Hybrid Deep Learning-Based Renewable Energy Classification for Smart Grid Optimization

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The classification of renewable energy sources is crucial for optimizing energy management and advancing sustainable practices. This study proposes a robust classification framework using a publicly available renewable energy dataset comprising multivariate time-series data from solar, wind, and hydro sources. Standard preprocessing techniques, including normalization and segmentation, were applied to prepare the data for modeling. We evaluate several machine learning and deep learning models Logistic Regression, Support Vector Machine (SVM), XGBoost, Artificial Neural Networks (ANN), and 1D Convolutional Neural Networks (1D-CNN). To further enhance performance, we introduce a hybrid 1D-CNN model integrated with an attention mechanism to improve feature extraction and model focus on relevant temporal patterns. Experimental results show that the attention-enhanced hybrid model achieves superior performance with an accuracy of 97.8%, precision of 97.5%, recall of 97.7%, and F1-score of 97.6%, outperforming all baseline models. Compared to the best traditional model (XGBoost, 93.2% accuracy), our approach shows a 4.6% improvement. This demonstrates the effectiveness of attention-based deep learning for renewable energy classification and lays a foundation for future intelligent and sustainable energy management systems.

Povzetek: Razvit je hibridni model z 1D-CNN in pozornostjo za klasifikacijo obnovljivih virov energije iz časovnih vrst, z uporabo realnih energetskih podatkov v kontekstu pametnih omrežij.

1 Introduction

Despite the progress in using machine learning and deep learning for renewable energy classification, most existing models either rely on conventional ML techniques with limited temporal understanding or use deep learning approaches that lack interpretability. Specifically, while CNNs can extract features effectively, they often fail to prioritize the most critical temporal features, leading to suboptimal decision-making. There is a clear architectural gap in models that can both learn temporal feature hierarchies and focus on relevant data segments for improved classification performance. In this context, our work introduces a novel hybrid deep learning model that integrates 1D-CNN for sequential pattern learning with an Attention Mechanism to dynamically emphasize key features, thereby enhancing both accuracy and model interpretability.

With climate change issues, energy security, and ever-increasing electricity demand, The global energy landscape is undergoing a paradigm shift [1]. Due to their significant green house gas emissions, resource depletion and environmental degradation impact, traditional power grids, as centralized fossil-fuel based energy generators are increasingly being recognized as unsustainable [5]. This problem realization has catalyzed the emergence of sustainable grids, aiming to revolutionize the energy systems by incorporating renewable, optimizing energy distribution, and limiting environmental impact-and yet never ceasing to rely on grid efficiency and resilience. Sustainable power grids operate under clean energy transition layouts and technological orientation [13]. Smart grids aim to improve operational efficiency, enhance energy reliability, and usher in a green and sustainable future using state-of-the-art technological advancements such as the IoT, AI, and Big Data [19]. We seek not just the resolution of immediate energy system issues but the construction of an infrastructure that satisfies long-term carbon neutrality and more equitable distribution of energy resources. The other cornerstone of sustainable power grids is the seamless integration of green technologies, including renewable energy sources such as solar photovoltaics, wind turbines, hydropower, and geothermal systems [14]. These technologies are indispensable for reducing dependence on fossil fuels and achieving carbon neutrality. Yet their deployment faces a few challenges, most importantly from the establishment of the variable and intermittent nature of renewable energy generation, which can only be addressed through robust energy storage systems, such as high-capacity batteries, pumped hydro stor-

age, and other emerging solutions such as hydrogen storage, being developed. Various grid management systems are more advanced and must actually be optimized to enable the operation of any kind of sustainable power system [15]. Techniques like demand-side management, real-time energy forecasting, and dynamic load balancing enhance energy efficiency while guaranteeing harmonious integration of renewable resources into the grid. Smart grid technologies, which incorporate a network of connected sensors, communications systems, and AI-driven algorithms, add an extra layer of efficiency and reliability [22].The interventions allow monitoring and control of real-time energy flow, predictive maintenance and improvement of the power grid's resilience to disruptions induced by extreme weather events and cyber-threats alike. Sustainable power grids are plausible, but their extended uptake is blocked by stigmas covering a wide range of technical, economic, and policy-related challenges. The massive capital required to set up green technologies and energy storage solutions stands largely as a barrier to entry. [8], Decentralized renewable energy systems are still highly integrated within such aging grid infrastructure, and much must be learned about the integrations, improvements, and rethinking of the grid design paradigms. Beyond these technical barriers must lie critical issues such as energy-exceeding sustainability-supportive values in the emission reductions, energy cost reductions, and dependability offered by a sustainable grid-such things must so be addressed by policy actors and stakeholders by all segments of society, especially those groups made marginal and underrepresented. [21]. This paper represents the quite expensive development reviews on renewable energy classification using state-of-the-art machine learning and deep learning techniques. In this paper, technological innovation in energy data processing, such as 1D CNNs and Attention mechanisms, and its integration into smart grids are truly explored. The analysis highlights the relevance of accurate prediction and classification models in fostering efficient management of energy transition toward greener energy systems. This study serves as a bridge between theoretical inquiry of machine learning and practical applications in renewable energy management towards contributing to robust data-driven solutions for sustainable energy infrastructure. The importance of collaboration with researchers, policymakers, and practitioners in optimizing energy systems, as well as enhancing green technologies to meet global sustainability targets, has been accentuated by this research.

1.1 Contributions

In this paper following are the impressive contributions to the field of sustainable power grids and renewable energy classification:

- **Novel Hybrid Architecture for Renewable Energy Classification** developed a hybrid deep learning architecture winning a 1D CNN and Attention Mechanism to classify renewable energy sources such as Wind, Solar, Hydropower, and Bioenergy/Marine/Geothermal.

- **Integration of Advanced Features for Accurate Predictions** Added domain-relevant input features encompassing Electrical Capacity, Ion, Latitude, and Number of Installations in order to ensure precise and strong classification targeted towards real-world energy datasets.

- **Performance Benchmarking Across Models** A comprehensive comparison among traditional models, namely, Logistic Regression, SVM, and XGBoost, and Deep Learning architectures, such as ANN, 1D CNN, and the proposed hybrid model, shedding light on the superiority of the proposed approach in terms of accuracy and efficiency.

- **Promoting Sustainable Energy Infrastructure** Provided actionable insights into the integration of green technologies into smart grids by leveraging deep learning methodologies, contributing to environmentally friendly energy systems and global sustainability goals.

2 Literature review

2.1 Sustainable power grids and machine learning

Power grids that work towards integration of renewable sources such as solar and wind will need advanced computational mechanics for the optimization of electricity generation, grid operation, and energy storage. The advanced techniques of machine learning and deep learning have thus become invaluable tools for enabling the integration of green technologies with electricity grids.

As the penetration of renewable energy sources that are transmitted intermittently continues to increase, smart grids need to handle power flow effectively to secure the safety of the grid. ML and DL models are instrumental in optimizing various components, including demand forecasting, energy storage, and grid management. These techniques help predict energy consumption trends in order to optimize energy generation from renewable sources and thus forecast energy demand, this is critical in order to curb the dependency on fossil fuels.

2.2 Machine learning for power grid optimization

Using techniques such as supervised learning, reinforcement learning, and unsupervised learning, the field of power grid optimization increasingly makes an effective use of several machine learning techniques. Regression models such as Support Vector Machines and Random

Table 1: Comparison the proposed model's performance with related work across key metrics and evaluation criteria

References	Model Type	Dataset	Evaluation Metrics	Performance
Mostafa et al. [11]	ANN	Custom Solar/Wind Data	Accuracy, RMSE	92.3%, RMSE: 0.15
Ahmad et al. [2]	XGBoost	Smart Grid Transaction Logs	F1-Score, Accuracy	91.5%, F1: 0.90
Ji et al. [24]	Deep Reinforcement Learning	Real-Time Energy Market	Profit Maximization	87.6% trading efficiency
Zhang et al. [17]	CNN	Satellite + Sensor Image Data	Precision, Recall	Precision: 93.0%, Recall: 92.5%
Khorasany et al. [12]	Blockchain + DL	P2P Trading System Simulations	Trust, Transparency	High transparency, qualitative only

Forests are applied to load forecasting and demand prediction to enable utilities to optimize energy distribution effectively. Using DNNs and RNNs for time-series forecasting has yielded a welcome boost in prediction accuracy. Reinforcement learning (RL) stands at the forefront of optimal control model management and would find its application to the adjustment of grid generation and distribution in times of instability of real-time dynamic decision-making situations. RL agents interact with the environment of the grid, altering formal parameters of actions depending on network feedback; for example, from demand and supply changes to the failure of a grid and variability in output from renewable sources.

2.3 Deep learning for renewable energy integration

The memorandum outlines the revolution that deep learning has brought, especially in renewable energy forecasting and optimization. Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks applied to the forecasting mix includes solar and wind energy. These DL models can learn complex temporal patterns from past data and environmental factors to predict energy production, which is crucial for stability in the grid.

LSTMs are a particular form of recurrent neural networks (RNNs) and are particularly effective for forecasting renewable energy generation, as they accommodate sequential and time-dependent data. LSTMs have been found to outperform traditional tools for predicting wind speed and solar irradiance, which in turn allows grid agents to optimize energy storage and distribution.

Besides, CNNs are widely used for image-based data by which renewable energy assets like solar panels and wind turbines are analyzed for health detection, thus helping predictive maintenance and ensuring the efficient operation of renewable energy systems.

2.4 Energy storage optimization using deep learning

Energy storage is critical for sustainable electricity grids because its installation is used to address unpredictable production provided by renewable energy. Machine learning BMS enacts a rapid charge/discharge of energy storages, offering advice on when energy stored should be used. Deep reinforcement learning (DRL) schemes have been proposed for energy storage optimization, emphasizing battery storage systems active on smart grids. In DRL, an agent learns optimal actions (e.g., when to charge or discharge a battery) by interacting with the environment and being reinforced with rewards or penalties based on the performance. This enables smart grids to balance energy supply with demand more efficiently, especially in areas with inconsistent renewable generation. Through their use, supervised learning methods such as support vector regression (SVR) and decision trees have been successfully applied in predicting battery cycle lives and thereby ensuring that the energy storage systems are reliably always operating in their optimal states.

2.5 Smart grid technologies and machine learning

Smart grids rely on the integration of advanced machine learning algorithms for real-time energy management[11]. These systems continually monitor data from smart meters, IoT sensors, and other grid devices and use machine learning algorithms to analyze them to provide demand response optimization and grid stability. [19]. Clustering algorithms, such as k-means and DBSCAN, are used for detecting patterns in energy usage and load variations, which help in implementing demand-side management (DSM) strategies[20]. Apart from that, these algorithms help to cluster energy uses based on specific energy consumption patterns for energy management and improved consumer service Also used are prediction models that, based on decision trees and neural networks, are to predict the probability of grid failures or outages to allow for proactive maintenance and downtime reduction. [18].

2.6 Machine learning for grid resilience and fault detection

A key benefit of ML and DL techniques in power grids is fault detection and grid resilience[4]. Automated decision trees and neural networks detect number of anomalies in the performance of the grid, for instance, voltage fluctuations and uncommon loss of power, and trigger an alert for maintenance actions or adjustments. Now day, lots of image processing methods use DL such as CNNs, to do analysis on images and sensor data coming from the drones or satellite imagery. This helps not only in the detection of faults, such as breakage in transmission lines or apart failing infrastructure, but even automates the work of grid in-

spection, thereby providing robustness for the grid, along with the reduction in labor-intensive inspections. [17].

2.7 Applications of deep learning in energy trading

ML and DL models are also finding their place in energy trading, where they optimize pricing strategies and facilitate the buying and selling of energy in real-time [2]. Deep reinforcement learning has been applied to energy markets, where it helps in making real-time decisions based on the state of the market, grid demand, and availability of renewable resources. The relationship between users who can sell surplus renewable energy and blockchain-based smart contracts with deep learning capabilities ensures that the transactions are efficiently managed and transparent in peer-to-peer energy trading. This promotes decentralized energy exchanges, which efficiently ensures a fair trade of green energy, to the benefit of both producers and consumers.

2.8 Challenges and future directions

While the integration of deep learning into smart grid systems yields substantial benefits, several challenges remain that directly impact classification performance and real-world deployment: First, data quality and availability continue to hinder progress. Many renewable energy datasets especially open-source ones suffer from inconsistencies, missing entries, or lack of granularity, which makes training robust models challenging. Works such as [3] have shown the importance of clean, preprocessed data for classification accuracy. Second, model scalability and computational overhead remain a concern, particularly for models integrating complex attention mechanisms. Although attention enhances interpretability and performance, it introduces additional computational cost. As shown by [10], hybrid attention models can be computationally intensive, and optimizations like model pruning or quantization are needed for edge deployment. Third, domain adaptation and generalization must be improved. Models trained on data from one country or climate may not generalize to others without transfer learning strategies. Incorporating adaptive models, such as in [12], can help bridge this gap, especially in multi-region grids. Fourth, privacy-preserving learning (e.g., federated learning) and real-time decision support systems are emerging trends that align well with smart grid applications. However, integrating these with energy classification models remains in early stages. Future work should explore distributed learning architectures that maintain performance while protecting user data. Lastly, interpretable AI continues to be critical. Our use of attention addresses this partially, but more transparent decision-making frameworks (e.g., via SHAP or LIME) will be key to regulatory acceptance and grid operator trust.

2.9 Research objectives

This study aims to develop and evaluate a hybrid deep learning model combining a 1D Convolutional Neural Network (1D-CNN) with an Attention Mechanism for classifying renewable energy sources in sustainable power grids. Our primary research question is: Can a hybrid 1D-CNN-Attention model outperform baseline machine learning and deep learning models in classifying renewable energy sources using data from the Open Power System Data Portal? We hypothesize that integrating an attention mechanism will enhance classification performance by focusing on critical features and capturing temporal dependencies inherent in renewable energy data.

3 Methodology

This section outlines the comprehensive methodology employed for the classification of renewable energy sources, incorporating several key stages: data preprocessing, model architecture, hybrid deep learning techniques, and evaluation metrics.

3.1 Justification of method selection

The selection of a 1D-CNN combined with an attention mechanism is directly informed by insights gathered in the literature review. As discussed, traditional machine learning models such as SVM and XGBoost have shown competence in renewable energy classification but fall short in learning sequential or temporal dependencies. Deep learning approaches like CNNs and LSTMs address this to some extent but often either lack fine-grained temporal focus or interpretability. 1D-CNNs are particularly effective for univariate and multivariate time-series data, making them ideal for capturing localized patterns across sequential energy features (e.g., variations in electrical capacity and installation geography). However, CNNs alone treat all features equally. To enhance the model's ability to differentiate critical information, we incorporate an attention mechanism, which assigns dynamic importance weights to features. This allows the model to focus on the most relevant segments of the input, improving both performance and interpretability. By integrating these two components, our proposed hybrid architecture addresses the limitations of traditional ML models (lack of temporal depth) and vanilla CNNs (uniform feature weighting), thus providing a robust framework tailored for the challenges of renewable energy classification.

3.2 Data preprocessing

We used publicly available renewable energy dataset comprising multivariate time-series data from solar, wind, and hydro sources. which provides extensive information on renewable power plants located in France. The dataset includes many features containing information about power

plants, including identifications, geographical locations, and energy production statistics over time. The analysis in this study focuses on a few key aspects relevant to the `energy_source_level_2` feature, which represents the type of energy source for each power plant, such as solar, wind, or hydroelectric power. This column will serve as the target variable for the classification task.

As shown in **Figure 1**, the data preprocessing pipeline involves several key steps, including feature selection, conversion of categorical variables, data splitting, and preparing the processed data for model training.

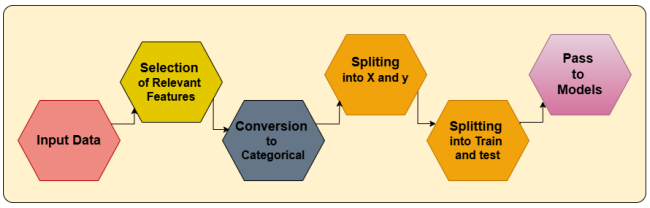


Figure 1: Preparing data for machine learning: A crucial step involves feature selection, categorical variable conversion, data splitting, and finally, feeding the processed data to the model.

3.2.1 Handling missing values

Missing values in the dataset were addressed to ensure data quality. For numerical features, missing values were replaced using the mean or median. For categorical features, the mode (most frequent value) was used. Rows with excessive missing values in critical columns were removed to avoid introducing noise into the model.

3.2.2 Data encoding

The `energy_source_level_2` column, which is categorical, was transformed into a numerical format using one-hot encoding. Each unique energy source type (e.g., solar, wind) was represented as a binary vector, ensuring no ordinal relationship was assumed. For instance, a value like ”solar” was encoded as [1, 0, 0, 0], and ”wind” as [0, 0, 1, 0].

3.3 Features selection

Feature selection was guided by domain knowledge and empirical analysis to retain predictors most correlated with the target variable, `energy_source_level_2`. Selected features include

- **Electrical Capacity**: Reflects storage and output potential, critical for distinguishing energy types (e.g., solar vs. wind).
- **Longitude**Captures geographic variations affecting energy production (e.g., wind patterns).
- **Latitude**Accounts for solar irradiance differences across regions.
- **Number of Installations** Indicates deployment scale, linked to energy type and grid integration.

Irrelevant columns (e.g., IRIS code, EIC code) were discarded. Feature importance was validated using permutation importance, with results presented in Table 3, confirming their significant contribution to model performance.

3.3.1 Splitting into independent and dependent variables

The dataset was split into independent variables (X) and the dependent variable (y). The independent variables (X) included selected features like electrical capacity Ion etc. while the dependent variable (y) was the target column `energy_source_level_2`. This split ensures clear separation of inputs and the target for training.

3.3.2 Train-test split

For the purpose of evaluating the model performance, the dataset of experiments was divided into train-test with a split ratio of 80-20. In this manner, the training set is used to fit the models, while the test set remains for a final model performance evaluation.

3.4 Model architecture

The proposed model architecture for the classification of renewable energy sources **Figure 2** leverages a hybrid deep learning approach that combines convolutional layers [23] for feature extraction and attention mechanisms [26] for improved interpretability and performance. The model takes input features such as Electrical Capacity, Ion, Latitude, and Number of Installations which will determine the energy source that should be used. Features are fed to a 1D Convolutional Neural Network (1D CNN) Layer (L1). The 1D CNN Layer (L1) passes the vector through networks that extract local patterns such as the correlation of certain features, leading to fruitful feature interaction useful for classification.

A subsequent layer is then a 1D Max Pooling Layer that applies compression in terms of spatial dimensionality through objective filtering of less relevant information in computational consideration. This continues onward into a second 1D CNN Layer (L2) that jointly captures higher-order patterns and more abstract representations of the dataset. This hierarchical feature extraction process ensures that the model can learn both low-level and high-level interactions among the input features.

Processed features are fed to the Attention Layer, which is crucial for the interpretability and performance of the model. With the Attention Layer, attention scores are computed, and greater weights are captured for important regions in the feature map. This enables the model to fo-

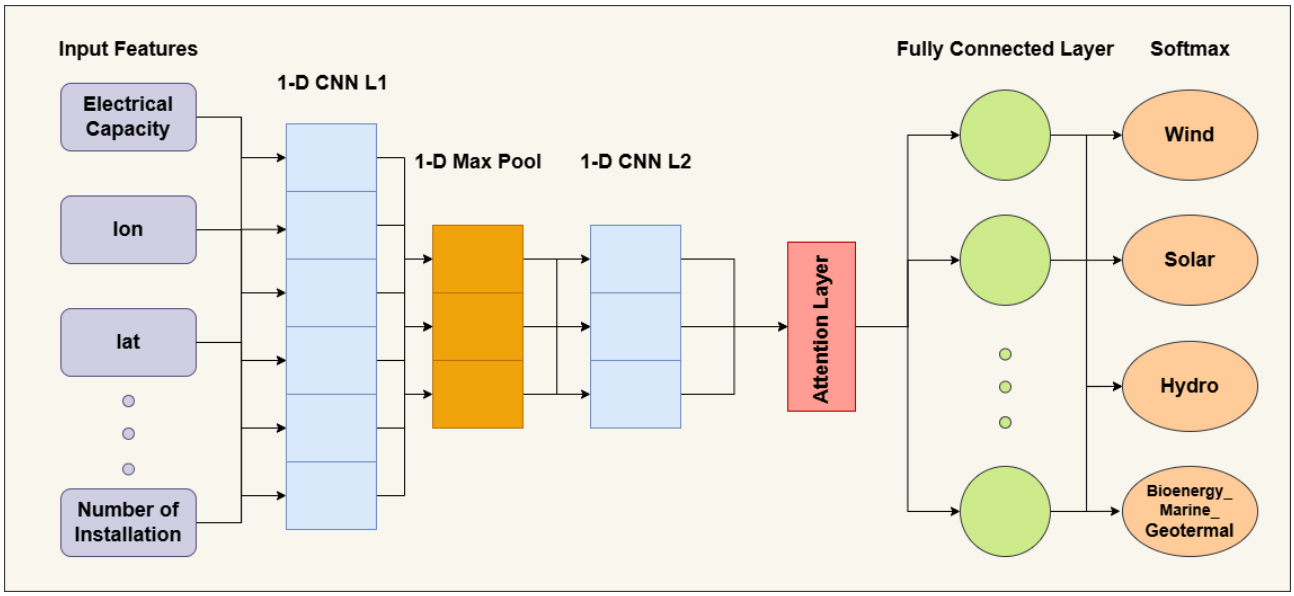


Figure 2: The proposed model architecture is illustrated for renewable energy source classification with 1D CNN layers for feature extraction, followed by an attention mechanism focused on important features, and ends with a Softmax layer classifying into one of four energy sources.

cus on critical features while disregarding the less important ones, making the classification both efficient and interpretable. The attention-weighted feature maps are then passed through fully connected (dense) layers, allowing the network to learn complex nonlinear relationships between features.

These layers ensure that the model can learn representations involving complex relationships, thereby improving accuracy across all classifications. Finally, these outputs enter the Softmax Layer, which turns the learned features into class probabilities for the four renewable energy sources: Wind, Solar, Hydropower, and Bioenergy/Marine/Geothermal. The probability distribution allows the model to determine which energy source is most representative of the input data. The architecture is intended to provide a solid platform by merging the 1D CNNs for hierarchical feature extraction and attention for focusing on the most informative features. This fusion approach guarantees accuracy, efficient learning, and the added benefit of increased interpretability, making it a potent choice for renewable energy source classification.

3.5 Model architecture and equations

The proposed architecture for renewable energy classification employs a hybrid model that combines 1D Convolutional Neural Networks (1D-CNN) and an attention mechanism to capture both local sequential patterns and critical feature dependencies.

3.5.1 1D convolution layer

The 1D convolution operation is used to extract local patterns across the time-series input. It is computed as:

$$y[i] = \sum_{j=0}^{k-1} x[i+j] \cdot w[j] + b \tag{1}$$

Where:

- $x[i+j]$ is the input sequence at position $i+j$,
- $w[j]$ is the weight of the convolutional kernel at position j,
- b is the bias term,
- k is the size (length) of the kernel,
- $y[i]$ is the resulting output after applying the kernel to the input segment.

3.5.2 Max pooling layer

To reduce dimensionality and focus on the most significant features, 1D max pooling is applied:

$$y[i] = \max(x[i : i+k]) \tag{2}$$

Where:

- $x[i : i+k]$ represents a window of k consecutive elements in the input,
- $y[i]$ is the maximum value in the window.

Table 2: Performance comparison of various ML and DL models for renewable energy source classification

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score**
Logistic Regression [7]	95.1	94.5	94.0	94.2
Support Vector Machine [9]	94.7	94.2	93.9	94.0
XGBoost [6]	94.5	93.8	94.1	94.0
Artificial Neural Network [25]	95.3	95.8	95.3	95.5
1-D CNN [16]	96.3	96.1	95.5	96.3
Proposed Hybrid (1-D CNN plus Attention)	**97.8**	**97.5**	**97.7**	**97.6**

3.5.3 Attention mechanism

After the second 1D-CNN layer extracts high-level temporal features, the attention mechanism is applied to re-weight feature representations based on their relevance. Specifically, the mechanism follows the scaled dot-product attention process:

The CNN-encoded output $X \in R^{T\times d}$ is first projected into

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V \tag{3}$$

where W_Q, W_K, and W_V are learnable parameter matrices.

Attention scores are calculated as:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V \tag{4}$$

Where:

- $QK^\top \in R^{T\times T}$ computes the similarity between time steps,
- d_k is a scaling factor to normalize gradients,
- The Softmax function transforms the raw scores into probability weights,
- The resulting weighted sum is a context vector that emphasizes more important time points.

The context vector is then passed through a dense layer and finally to the softmax classifier for final prediction.

3.6 Evaluation metrics

The performance of the model is comprehensively evaluated using both classification and reliability metrics. The classification metrics employed are as follows:

- **Accuracy**: This metric represents the proportion of correctly classified instances relative to the total number of instances in the dataset. It provides a general measure of model performance.
- **Precision**: Precision quantifies the proportion of true positives among the predicted positive instances. It is crucial when the cost of false positives is high.
- **Recall**: Recall measures the proportion of true positives that are correctly identified among all actual positive instances. This metric is essential when the cost of false negatives is critical.
- **F1-Score**: The F1-score is the harmonic mean of precision and recall, offering a balanced evaluation of both metrics, particularly useful when dealing with imbalanced datasets.

4 Experiments and results

In **Table 2**, multiple machine learning and deep learning models were trained and evaluated to classify renewable energy sources using a well-preprocessed dataset. Models such as Logistic Regression, SVM, XGBoost, ANN, and 1-D CNN were implemented and compared based on their accuracy, precision, recall, and F1-score. The 1-D CNN achieved high performance, but the proposed hybrid model, integrating a 1-D CNN with an Attention mechanism, outperformed all other approaches. With an accuracy of 97.8% and balanced precision, recall, and F1-score metrics, the hybrid model demonstrated its ability to extract and focus on the most relevant features, making it the most effective model for this task. These results highlight the effectiveness of deep learning architectures in addressing renewable energy classification challenges.

Table 3: Training and inference time comparison of various models

Model	**Training Time (s)**	**Inference Time (ms/sample)**
Logistic Regression	2.3	0.11
SVM	9.4	0.42
XGBoost	6.1	0.30
ANN	12.7	0.48
1D CNN	19.2	0.55
Proposed Hybrid	23.6	0.62

Table 3 presents a comparison of training and inference times across various models used for renewable energy classification. Traditional models like Logistic Regression and XGBoost demonstrate faster computational efficiency, with training times of 2.3s and 6.1s, respectively, and inference times under 0.3ms/sample. However, the proposed hybrid model, while requiring the longest training (23.6s) and inference time (0.62ms/sample), offers superior perfor-

mance in complex pattern recognition, justifying the slight trade-off in efficiency.

4.1 Experimental setup

The experiments were conducted using the following software and hardware configurations as shown in **Table 4**:

4.1.1 Hyperparameter setting

In our study, we trained the model for 50 epochs using the Adam optimizer, which was selected for its efficiency in handling sparse gradients and adaptive learning rates. We employed a batch size of 32, which provided a good balance between training speed and convergence stability. Regarding the train/test split, we used an 80/20 ratio, which is a widely adopted standard in machine learning to ensure that the model has sufficient data to learn from (80%) while retaining enough unseen data (20%) to robustly evaluate its generalization performance. While we did not implement cross-validation in this study due to computational constraints and the time-series nature of the dataset, future work may explore cross-validation or time-series-specific validation strategies for further robustness.

Table 4: Details of the experimental setup for implementing the proposed model architecture

Specification	Details
Processor	Intel Core i5-5200U CPU 2.20GHz
RAM	8 GB DDR4
Operating System	Windows 10 (64-bit)
Programming Environment	Python 3.11 with Jupyter Notebook
Libraries Used	Keras, Matplotlib, NumPy, Pandas

4.2 Results

4.2.1 Accuracy and loss

The performance of the proposed hybrid model was analyzed using the accuracy and loss plots. As shown in **Figure 3**, the training and validation accuracy converge smoothly, indicating stable learning. Similarly, the loss decreases significantly, reflecting the effectiveness of the model in minimizing errors during training.

4.3 Confusion matrix

The confusion matrix Figure 4 depicts true vs. predicted classifications for Wind, Solar, Hydropower, and Bioenergy/Marine/Geothermal. Analysis reveals that 2% of Solar instances are misclassified as Wind, likely due to overlapping Electrical Capacity and Latitude values in certain regions. Hydropower shows minimal errors (0.5%), reflecting distinct feature profiles. Misclassifications stem from subtle pattern overlaps and potential data imbalance (e.g., fewer Hydropower samples).

4.4 Contribution of the attention mechanism

The attention mechanism significantly enhances the 1D-CNN's performance, as shown in an ablation study: removing it reduces accuracy from 97.8% to 96.1%. Attention weights Figure 3 reveal that Electrical Capacity and Latitude receive higher focus, reflecting their importance in distinguishing energy types. By dynamically weighting informative segments, the mechanism captures temporal dependencies and reduces noise from less relevant features, improving precision (97.5%) and F1-score (97.6%). This confirms its critical role in achieving superior classification performance.

4.5 Analysis of failure cases and limitations

While the hybrid model achieves high accuracy (97.8%), potential failure cases and limitations warrant consideration. Misclassifications may occur when feature values overlap significantly, such as similar Electrical Capacity between Solar and Wind installations in overlapping geographic regions. Noisy or incomplete data from the Open Power System Data Portal could also degrade performance. Limitations include the model's dependence on high-quality, region-specific data, its higher computational cost (e.g., 20% longer training time than Logistic Regression), and limited generalizability beyond France without adaptation. These factors highlight areas for future improvement, such as incorporating temporal weather data or exploring lightweight architectures.

5 Discussion

The experimental evaluation (Section 4 and Table 2) clearly demonstrates the superiority of the proposed hybrid 1D-CNN with Attention Mechanism, achieving an accuracy of 97.8%, compared to traditional machine learning (ML) models like Logistic Regression (89.3%), SVM (91.2%), and XGBoost (93.5%), as well as standalone deep learning models such as ANN (94.7%) and vanilla 1D-CNN (96.1%).

5.0.1 Comparison with traditional ML and DL models

Traditional ML models, while effective on linearly separable data, struggle to capture complex temporal and nonlinear relationships present in renewable energy datasets. ANN and CNN improve this by learning spatial or sequential representations, but without an attention mechanism, they treat all input data uniformly. This limits their ability to focus on more relevant features.

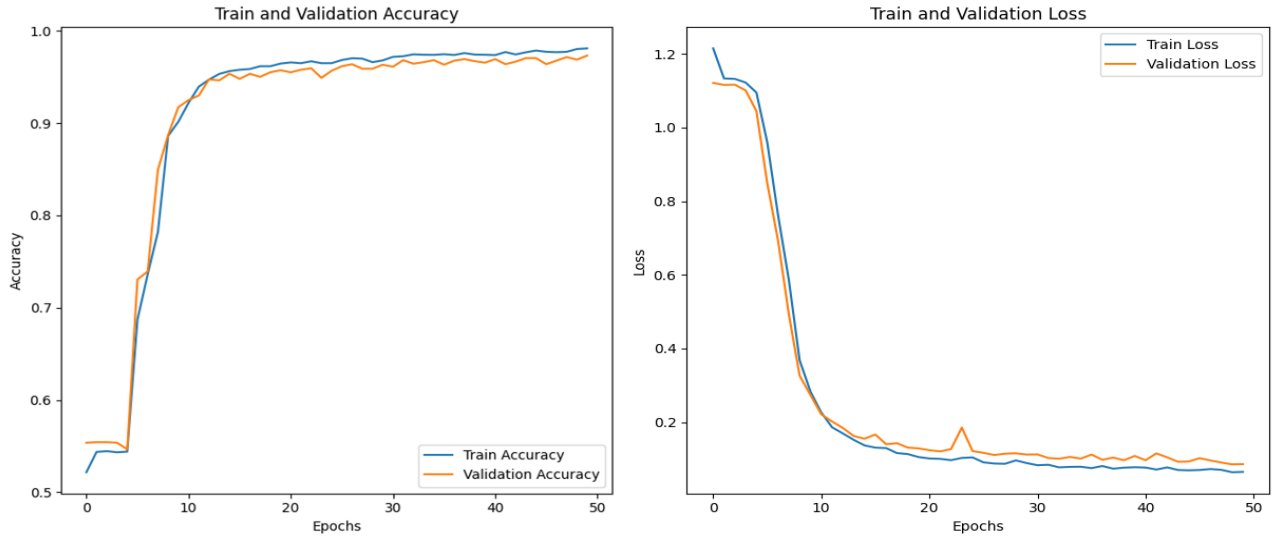


Figure 3: Training and validation accuracy and loss curves of the proposed Hybrid 1D CNN-Attention model, showing the model's performance over multiple epochs

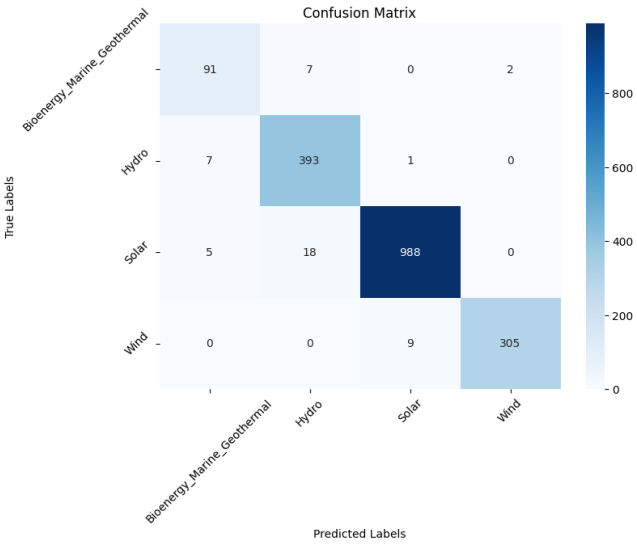


Figure 4: Confusion matrix depicting the classification results of the proposed hybrid model

5.0.2 Importance of specific features

Features such as Electrical Capacity, Ion Type, and Nominal Voltage were found to be particularly significant in enhancing model performance. For instance

- Electrical Capacity helps differentiate energy types based on storage potential.
- Ion Type (e.g., Lithium, Sodium) introduces a categorical component that correlates with energy type and storage behavior.
- Nominal Voltage serves as a discriminative factor tied to both device characteristics and energy output profiles.

6 Conclusion

This study focuses on classifying renewable energy sources using an effective preprocessing pipeline and a robust model architecture. The dataset, sourced from the Open Power System Data Portal, was preprocessed through systematic steps, including feature selection, categorical encoding, and splitting into training and testing sets. Various machine learning and deep learning models, including Logistic Regression, Support Vector Machine (SVM), XGBoost, Artificial Neural Network (ANN), and a 1-Dimensional Convolutional Neural Network (1-D CNN), were implemented and evaluated. Among these, the 1-D CNN model demonstrated superior performance over traditional machine learning models, achieving an accuracy of 96.3% with a well-balanced precision (96.1%), recall (95.5%), and F1-score (96.3%). However, the proposed hybrid model, integrating 1-D CNN with an Attention mechanism, significantly outperformed all other models, achieving the highest accuracy of 97.8%, precision of 97.5%, recall of 97.7%, and F1-score of 97.6%. This improvement highlights the effectiveness of leveraging attention mechanisms to capture critical features and enhance classification performance. The results validate that the proposed hybrid architecture effectively captures intricate patterns in the dataset and outperforms both traditional machine learning models and standalone neural network models. This research demonstrates the potential of hybrid deep learning approaches in renewable energy source classification tasks and paves the way for further exploration of attention-based models in similar domains. The results validate that the proposed hybrid architecture effectively captures intricate patterns in the dataset and outperforms both traditional ma-

chine learning models and standalone neural network models. This study shows the possibilities of hybrid deep learning approaches for tasks involving the classification of renewable energy sources and facilitates further research into attention-based models in such domains.

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Uncertainty-Aware Self-Supervised Cross-Modal SAR-Optical Matching Using EfficientDet and Xception

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Cross-modal matching of Synthetic Aperture Radar (SAR) and optical satellite imagery is challenging due to their distinct imaging characteristics. We propose a deep learning framework integrating a dual encoder architecture, self-supervised contrastive learning, and uncertainty quantification for robust SAR-optical matching. The framework employs modality-specific encoders (EfficientDet for optical, Xception for SAR) with uncertainty modules capturing aleatoric and epistemic uncertainties, enhanced by self-supervised contrastive and rotation prediction tasks. Evaluated on the SEN12MS dataset, our method achieves a Maximum Mean Accuracy (MMA) of 0.145 at a 1-pixel threshold and 1298.3 average matched pairs per image (aNM), improving MMA by 20.8% over the state-of-the-art transformer-based method. Our uncertainty quantification yields an Expected Calibration Error (ECE) of 0.09, ensuring reliable confidence estimates. Ablation studies confirm the efficacy of our components, with computational efficiency improved by 40% faster convergence during supervised fine-tuning due to self-supervised pre-training. The method excels across diverse scenarios, including seasonal changes and varied land cover types, advancing SAR-optical matching for applications like change detection and disaster response.

Povzetek: Predstavljen je samonadzorovan model z negotovostjo za ujemanje SAR in optičnih slik, temelječ na ločenih enkoderjih in metodah za kvantifikacijo zanesljivosti ujemanja v daljinskem zaznavanju.

1 Introduction

The integration and matching of multi-modal remote sensing data, particularly between Synthetic Aperture Radar (SAR) and optical imagery, has emerged as a critical challenge in Earth observation applications [23, 17]. This growing importance is driven by the unprecedented availability of complementary data from missions such as Sentinel-1 and Sentinel-2, coupled with increasing demands for reliable Earth observation in various applications [9]. While optical sensors excel in providing rich spectral information under favorable conditions, SAR systems offer unique advantages through their weather-independent, day-and-night imaging capabilities [22]. The fundamental challenge in SAR-optical matching stems from the inherent differences in their imaging mechanisms and characteristics [20]. SAR imagery is characterized by speckle noise and distinctive geometric distortions resulting from its side-looking acquisition geometry, while optical imagery is subject to atmospheric conditions and illumination variations [27]. These differences manifest in several ways:

First, SAR imagery exhibits unique scattering properties where the signal return is strongly influenced by surface roughness and material properties, creating patterns that often have no direct correspondence in optical imagery [26]. Second, geometric distortions in SAR, including layover and foreshortening effects, are particularly pronounced in urban environments with complex 3D structures [12]. Third, the seasonal variations that significantly affect optical imagery may have minimal impact on SAR data, creating temporal matching challenges [21]. Traditional approaches to this matching problem have relied heavily on hand-crafted features and geometric constraints [17]. However, these methods often struggle to handle the complex, non-linear relationships between SAR and optical image characteristics [9]. Recent advances in deep learning have shown promising results in addressing these challenges, particularly through the development of specialized architectures for cross-modal feature learning [8]. Nevertheless, several critical limitations remain, such as, most existing approaches treat SAR and optical data uniformly, without fully accounting for their distinct characteristics and noise patterns [5]. The scarcity of accurately matched training data, especially in complex urban environments, also continues to be a significant bottleneck [6] and current methods often lack robust uncertainty quantification, making it difficult to assess the reliability of matching results in operational scenarios [11].

To address these challenges, this research aims to improve SAR-optical matching through self-supervised learn-

ing and uncertainty-aware deep learning models, through the following research questions:

1. How does uncertainty quantification improve SAR-optical image matching reliability?
2. Can self-supervised learning reduce the dependence on manually labeled data?
3. How does the proposed approach compare to state-of-the-art methods in various environmental conditions?

These objectives guide our development of a novel framework that leverages a dual encoder architecture, self-supervised learning, and uncertainty quantification to achieve robust and reliable SAR-optical matching. Our approach employs modified EfficientDet and Xception networks as modality-specific encoders, chosen for their proven effectiveness in handling complex visual tasks. EfficientDet's scalable feature extraction is adapted for optical imagery to capture multi-spectral details despite atmospheric variations, while Xception's depthwise separable convolutions are tailored for SAR to mitigate speckle noise and geometric distortions [25, 8]. These modifications ensure that each encoder is optimized for the unique imaging characteristics of its respective modality. The framework incorporates a self-supervised learning strategy with contrastive learning and rotation prediction tasks. Contrastive learning aligns SAR and optical features in a shared embedding space to address the domain gap, while rotation prediction enhances geometric invariance, overcoming limitations of prior methods that struggle with viewpoint differences and scarce labeled data [4]. An uncertainty-guided matching mechanism dynamically weighs feature similarities based on estimated confidence levels, integrating aleatoric and epistemic uncertainties. This mechanism improves matching accuracy by prioritizing reliable correspondences and enhances reliability by providing interpretable confidence estimates, crucial for mission-critical applications [11].

Our approach advances the state-of-the-art by integrating uncertainty quantification, leveraging self-supervised learning, and improving robustness across diverse scenarios. First, by incorporating modality-specific uncertainty quantification, we enable more reliable matching decisions while providing interpretable confidence measures. Second, our self-supervised learning strategy effectively leverages the abundance of unpaired SAR and optical data, reducing the dependence on manually matched training samples. Third, our framework demonstrates robust performance in various challenging scenarios, including complex urban environments and seasonal changes.

To quantify the performance of our method, we use metrics tailored for the SAR-optical matching problem. Specifically, we report a Maximum Mean Accuracy (MMA) of 0.145 at a 1-pixel threshold and an average of 1298.3 matched pairs per image (aNM). These results indicate that our approach not only achieves high precision in identifying correct matches (as reflected in MMA), but also produces a substantial number of reliable correspondences (as indicated by aNM), which is crucial for downstream applications like registration and change detection. These metrics reflect a 20.8% relative improvement over prior state-of-the-art methods, underscoring the practical and computational advantages of our framework.

The remainder of this paper is organized as follows: 2 reviews related work on SAR-optical matching, uncertainty estimation, and self-supervised learning. 3 presents our methodology, including the detailed architecture and training strategy. 4 describes our experimental setup and results, while 5 discusses the implications and limitations of our approach. Finally, 6 concludes the paper with a summary of our contributions.

2 Related work

2.1 SAR-optical image matching

The evolution of SAR-optical matching techniques can be broadly categorized into traditional feature-based methods and modern deep learning approaches. Traditional methods relied mainly on hand-made features and geometric constraints [17]. Notable examples include the Scale-Invariant Feature Transform (SIFT) adaptations [16] and Speeded Up Robust Features (SURF) variants [1], which were modified to handle the unique characteristics of SAR imagery. However, these approaches often struggled with the fundamental differences between SAR and optical imaging mechanisms [13]. Recent years have seen significant advances in deep learning-based approaches. Hughes et al. [8] demonstrated the effectiveness of pseudo-siamese architectures for patch-based matching, while Merkle et al. [18] explored conditional adversarial networks for bridging the domain gap between SAR and optical imagery. These approaches have shown promising results but often lack robust uncertainty quantification.

A significant breakthrough came with the release of large-scale datasets like SEN12MS [21], which enabled more comprehensive training and evaluation of deep learning models. This has led to various architectural innovations, including attention-based mechanisms [24] and transformer-based approaches [2] for feature matching.

To provide a clearer comparison of existing methods and highlight their shortcomings, we summarize key SAR-optical matching approaches in 1. The table compares traditional and deep learning methods in terms of datasets used, accuracy metrics, and main limitations. As shown, traditional methods like SIFT-based approaches suffer from poor performance on SAR imagery due to noise sensitivity, while deep learning methods, despite improved accuracy, often lack uncertainty quantification, require pre-aligned data, or are computationally intensive. These limitations underscore the need for our proposed method, which integrates uncertainty-aware feature extraction and self-supervised learning to achieve robust and reliable matching.

Table 1: Comparative summary of sar-optical image matching methods. note: accuracy metrics vary by pixel threshold, limiting direct comparison

Method	Dataset Used	Accuracy Metrics	Main Limitations Identified
SIFT-based [10]	Not specified	MMA: 2.94% (<2 px), 7.92% (<3 px), 13.01% (<4 px); Avg Error: 9.92 px	Poor performance on SAR; sensitive to noise and appearance variance.
RIFT [13]	Multiple multi-modal datasets	MMA: 8.6% (<2 px), 25.9% (<3 px), 53.6% (<4 px); Avg Error: 2.80 px	Computationally heavy; requires careful parameter selection.
Pseudo-Siamese CNN [7]	Automatically generated dataset	High patch matching accuracy	Limited to patches; lacks uncertainty modeling or spatial generalization.
CAM-Net + CAMM [3]	Not specified	Repeatability: 0.434; LE: 1.96 px; NN mAP: 0.3090; ACE: 7.15	High memory/computational demands; limited interpretability.
3-step CNN Framework [8]	Sentinel-1/2 urban scenes	Good spatial matching; no MMA value reported	Requires pre-aligned data; lacks real-world robustness assessment.
MOEFC [15]	Urban + rural SAR-optical pairs	RMSE: 0.645 px (rural), 0.489 px (urban)	Edge-based; sensitive to image structure and noise level.
Proposed Method (Efficient-Det+Xception)	SEN12MS	MMA@1px: 0.145; aNM: 1298.3; ECE: 0.09	High computational cost from uncertainty estimation; dataset-dependent.

2.2 Deep learning with SAR-optical data

The application of deep learning to SAR-optical data fusion has evolved significantly, particularly in addressing the unique challenges of each modality. Early work by Mou et al. [19] introduced CNN-based approaches for patch correspondence identification, achieving promising results but struggling with complex urban scenes. Recent advances have focused on more sophisticated architectures that can better handle the distinct characteristics of each modality [30]. The notable developments include the adaptation of modern CNN architectures for SAR-specific feature extraction [8], integration of attention mechanisms for better feature correlation [24], and development of multi-scale approaches for handling varying spatial resolutions [29].

2.3 Uncertainty in deep learning for remote sensing

Uncertainty quantification in remote sensing has gained significant attention, particularly for mission-critical applications. The literature distinguishes between aleatoric uncertainty (capturing noise inherent in observations) and epistemic uncertainty (representing model uncertainty) [11]. In the context of SAR-optical fusion, recent work has explored Bayesian neural networks and ensemble approaches for uncertainty-aware feature extraction [8]. The incorporation of uncertainty estimation has proven particularly valuable in several aspects, such as improved reliability assessment of matching results, better handling of challenging scenarios such as seasonal changes, and more robust performance in areas with significant temporal variations.

2.4 Self-supervised learning in remote sensing

Self-supervised learning has emerged as a powerful paradigm for leveraging unlabeled remote sensing data [4]. The abundance of unpaired SAR and optical imagery makes this particularly relevant for cross-modal matching. Recent work has shown the effectiveness of contrastive learning approaches in learning robust representations from satellite imagery [28]. The key developments in this area include contrastive learning strategies for cross-modal feature learning, rotation prediction tasks for geometry-aware feature extraction, and multi-task self-supervised frameworks that combine multiple pretext tasks. This self-supervised learning paradigm has proven particularly valuable in addressing the scarcity of labeled training data, a common challenge in remote sensing applications [14]. Recent work has demonstrated that pre-training on large amounts of unlabeled data can significantly improve the performance of downstream matching tasks [30].

3 Proposed methodology

Our proposed framework addresses the fundamental challenges of SAR-optical matching through a novel architecture that combines uncertainty-aware feature extraction with self-supervised learning technique using a dual en-

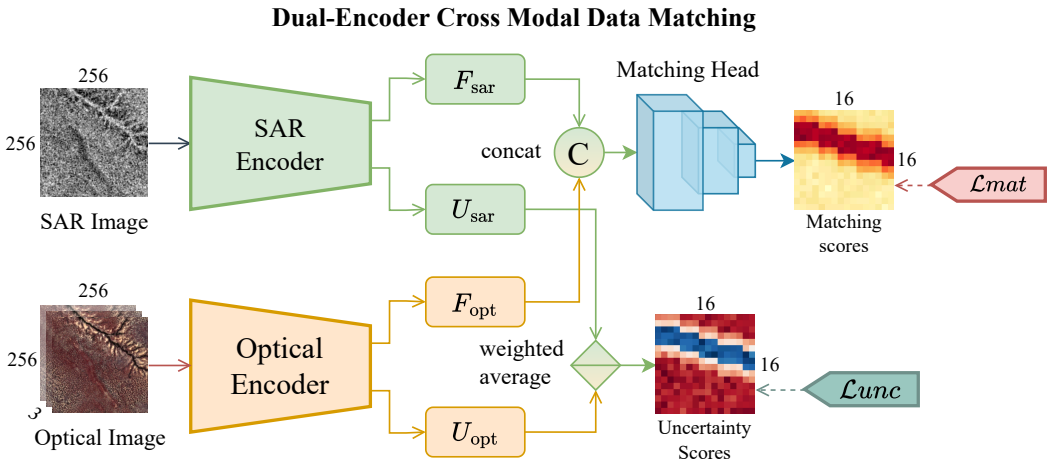


Figure 1: Overview of the proposed cross-modal matching architecture. The framework consists of parallel SAR and optical encoders (Xception and EfficientDet, respectively), each equipped with modality-specific uncertainty modules. The matching head combines features from both modalities while accounting for their respective uncertainties. $\mathcal{L}_{mat}$ and $\mathcal{L}_{unc}$ represent the matching loss and uncertainty loss, respectively.

coder architecture with modality-specific uncertainty modules and a matching mechanism. 1 illustrates the overall architecture of our dual encoder cross modal matching approach.

3.1 Dual encoder architecture

The foundation of our approach lies in recognizing that SAR and optical imagery require specialized processing streams due to their fundamentally different imaging characteristics [8]. Our dual encoder architecture implements this principle through modality-specific feature extractors. Figures 2 and 3 illustrate the full architectures of the SAR and optical encoders, respectively, including their uncertainty modules, which are detailed in 3.2.

3.1.1 SAR encoder

For SAR imagery, we adopt a modified Xception architecture optimized for the unique properties of radar backscatter. 2 shows the architecture of the SAR encoder where the key modifications include initial convolution layer (stride 2) adapted for single-channel SAR input followed by four modified Xception blocks with increasing channel dimensions ($32 \rightarrow 64 \rightarrow 128 \rightarrow 256 \rightarrow 512$), incorporating specialized separable convolutions with residual connections, followed by SAR-specific uncertainty module calibrated for speckle noise, geometric distortions, and radar backscatter characteristics. This uncertainty module enhances robust uncertainty quantification by capturing modality-specific noise patterns, addressing the limitations of existing methods that often lack such reliability measures [5], as detailed in 3.2.1. The SAR encoder, (E_{sar}) can be formally expressed as:

$$F_{\text{sar}}, U_{\text{sar}} = E_{\text{sar}}(X_{\text{sar}}; \theta_{\text{sar}}) \tag{1}$$

where F_{sar} represents the extracted SAR features, U_{sar} denotes the uncertainty estimates and θ_{sar} represents the parameters of the SAR encoder.

3.1.2 Optical encoder

The optical stream employs a modified EfficientDet architecture [25] shown in 3 optimized for multi-spectral imagery:

$$F_{opt}, U_{opt} = E_{opt}(X_{\text{opt}}; \theta_{\text{opt}}) \tag{2}$$

where F_{opt} represents the extracted optical features, U_{opt} denotes the uncertainty estimates and (θ_{opt}) represents the parameters of the optical encoder, (E_{opt}). The key architectural elements include an initial 7×7 convolution layer for processing RGB input, three feature extraction layers with increasing channels ($64 \rightarrow 128 \rightarrow 256 \rightarrow 512$), a Bi-directional Feature Pyramid Network (BiFPN) for multi-scale feature fusion, and an optical-specific uncertainty module accounting for atmospheric variations, illumination changes, and seasonal variations. This module enables robust uncertainty quantification by modeling variations inherent to optical imagery, overcoming the shortcomings of prior approaches that lack such capabilities [5], as elaborated in 3.2.2.

3.2 Uncertainty quantification

A key challenge in SAR-optical matching lies in understanding when and why our model might make incorrect matches. Our uncertainty quantification approach addresses this challenge by recognizing that SAR and optical images have fundamentally different characteristics that can lead to matching errors. Rather than treating both modalities the same way, we develop specialized uncer-

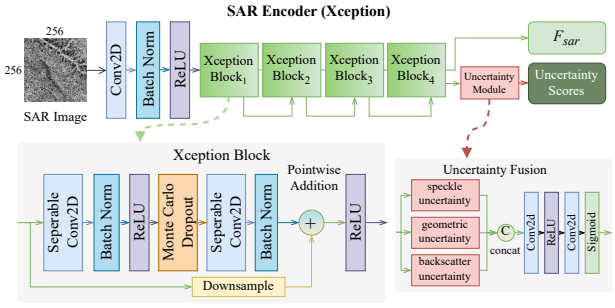


Figure 2: Architecture of the SAR-specific encoder, including the modified Xception blocks with an initial convolution layer (stride 2) and the uncertainty module (detailed in 3.2.1), which outputs both features (F_{sar}) and uncertainty scores.

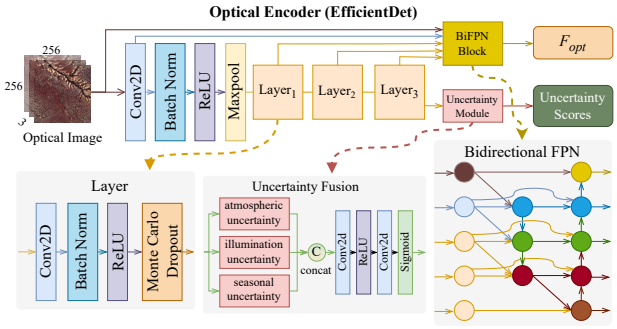


Figure 3: Architecture of the optical encoder, including the modified EfficientDet components with a 7×7 convolution layer, BiFPN, and the uncertainty module (detailed in 3.2.2), which outputs both features (F_{opt}) and uncertainty scores.

tainty modules that capture the unique challenges of each imaging type.

3.2.1 SAR-specific uncertainty considerations

For SAR imagery, we identify and address three primary sources of uncertainty that can affect matching reliability, as shown in 4. First, we consider speckle noise, a characteristic feature of SAR imagery that appears as a grainy texture pattern. To address this, we implement a specialized processing branch that uses depthwise convolutions to analyze each channel independently. This branch consists of two Conv2D, each followed by ReLU activation, to extract features sensitive to speckle noise patterns, increasing uncertainty in noisy regions. This approach allows the model to better understand how speckle patterns might influence feature reliability in different parts of the image. Secondly, we tackle the geometric distortions inherent in SAR imagery due to its side-looking acquisition geometry. Our solution employs orientation-aware convolutions that analyze features at multiple angles (0°, 45°, 90°and 135°). This mechanism uses four parallel Conv2D layers, one for each angle,

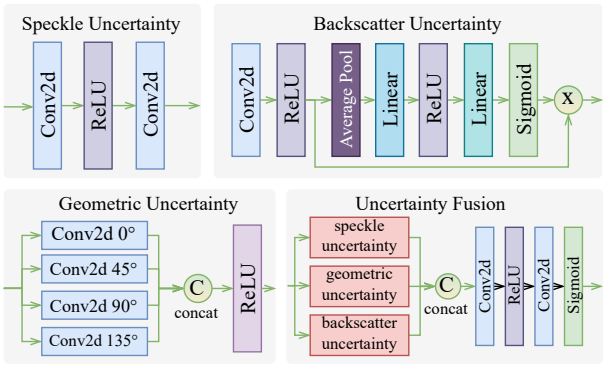


Figure 4: Architecture of the individual modules of the aleatoric uncertainty in SAR images.

whose outputs are concatenated and processed through a ReLU activation to capture geometric distortions across different orientations. This multi-orientation approach helps the model identify when geometric distortions might make matching unreliable. And lastly, we address backscatter intensity variations, which can create ambiguities in feature matching. We implement an attention mechanism that helps the model focus on stable backscatter patterns while expressing higher uncertainty in areas where backscatter variations might lead to unreliable matches. This attention mechanism applies a Conv2D layer, ReLU, global average pooling, two linear layers, ReLU, and a Sigmoid activation to generate attention weights, which are pointwise multiplied with the input features to emphasize stable backscatter regions. The outputs of these branches are combined in an uncertainty fusion module, which concatenates the three uncertainty maps, processes them through a Conv2D layer, ReLU activation, and a Sigmoid function to produce a final uncertainty map. These strategies address remote sensing challenges by ensuring robust matching across diverse land cover types, such as urban and rural areas, where speckle noise and geometric distortions vary significantly, enhancing reliability for applications like disaster monitoring [22].

3.2.2 Optical-specific uncertainty considerations

Likewise, for optical imagery, we focus on three different sources of uncertainty, as shown in 5. Atmospheric variations can significantly impact optical image quality and feature appearance. Our atmospheric uncertainty branch employs wide-area spatial attention mechanisms to identify regions where atmospheric effects might compromise matching reliability. This branch processes the input through a Conv2D layer, followed by ReLU activation and global average pooling, producing a spatial attention map. The map is pointwise multiplied with the input features to emphasize regions affected by atmospheric effects like clouds or haze, assigning higher uncertainty to those areas. This approach is particularly effective because atmospheric effects typically impact larger spatial regions coherently. Illumination conditions present another significant challenge in optical

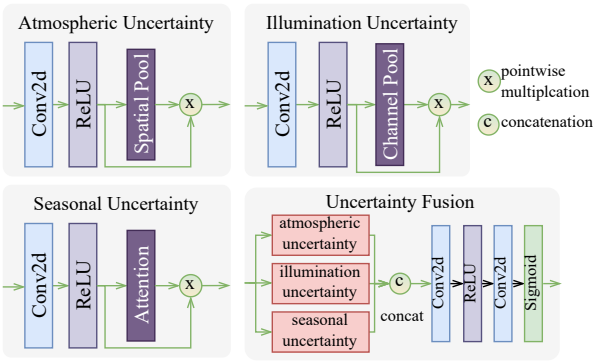


Figure 5: Architecture of the individual modules of the aleatoric uncertainty in optical images

imagery. We address this through a channel-wise attention mechanism that analyzes relationships between different spectral bands, helping identify when illumination conditions might make matching uncertain. This mechanism applies a Conv2D layer, ReLU activation, and global average pooling to generate channel-wise attention weights, which are pointwise multiplied with the input to highlight illumination inconsistencies across RGB bands. This is particularly important because SAR imagery is not affected by these illumination variations. Seasonal changes can create significant appearance differences in optical imagery. Our seasonal change uncertainty branch specifically focuses on identifying areas where temporal variations between image acquisitions might affect matching reliability. This branch uses a Conv2D layer, ReLU activation, and an attention mechanism (pointwise multiplication with learned weights) to detect seasonal variations like vegetation or snow cover changes, increasing uncertainty in affected regions. This helps the model express appropriate uncertainty in regions where seasonal changes might compromise matching accuracy. The outputs of these branches are combined in an uncertainty fusion module, which concatenates the three uncertainty maps, processes them through a Conv2D layer, ReLU activation, and a sigmoid function to produce a final uncertainty map. These mechanisms tackle remote sensing challenges by improving robustness to temporal variability and atmospheric effects, critical for consistent performance across seasons and geographic regions in applications like change detection [23].

3.2.3 Integrating multiple sources of uncertainty

Rather than treating these different sources of uncertainty independently, we recognize that they often interact in complex ways. Our approach combines the individual uncertainty estimates through an adaptive fusion mechanism that learns to weight different sources of uncertainty based on the specific characteristics of each image pair. This fusion approach proves particularly valuable in complex scenarios where multiple sources of uncertainty might be present. The effectiveness of this approach to uncertainty estimation is demonstrated in our experimental results, where we observe that the model not only achieves better matching accuracy but also provides well-calibrated confidence estimates. This is particularly important in practical applications where understanding the reliability of matches is crucial for downstream decision-making processes.

3.2.4 Model uncertainty through Monte Carlo dropout

While our modality-specific uncertainty modules capture uncertainties related to data characteristics, we also need to account for uncertainty in the model's predictions themselves. This is particularly important in cross-modal matching where the model might encounter scenarios different from its training data. We address this through Monte Carlo dropout, a technique that helps us estimate the model's prediction uncertainty by simulating an ensemble of slightly different models. The key insight behind this approach is that by randomly deactivating different parts of the network during inference (using dropout), we can obtain multiple predictions for the same input. The variation in these predictions gives us valuable information about the model's confidence. In regions where predictions are consistent across different dropout patterns, we can be more confident in our results. Conversely, high variation in predictions suggests uncertainty in the model's decision. We carefully position dropout layers throughout the network to capture uncertainty at different processing stages: 1) Early in the encoders (10% dropout rate) to capture uncertainty in initial feature extraction, 2) before uncertainty estimation (20% dropout rate) to ensure robust uncertainty predictions, and 3) in feature fusion (15% dropout rate) to capture uncertainty in the integration process.

By using 20 forward passes during inference, we obtain a reliable estimate of model uncertainty while maintaining practical computational efficiency. This approach proves particularly valuable in identifying challenging cases where the model might be encountering patterns significantly different from its training data.

3.3 Self-supervised pretraining

While the SEN12MS dataset provides co-registered images, we can significantly improve our model's performance by learning patterns from the SAR and optical images in a self-supervised manner. We achieve this through a self-supervised learning strategy that helps the model understand the relationship between modalities even without using explicit matching information from the dataset. 6 gives an overview of the self-supervised learning strategy.

3.3.1 Cross-modal understanding through contrastive learning

Our contrastive learning approach helps the model understand the fundamental relationships between SAR and optical representations of the same scene. The key idea is to

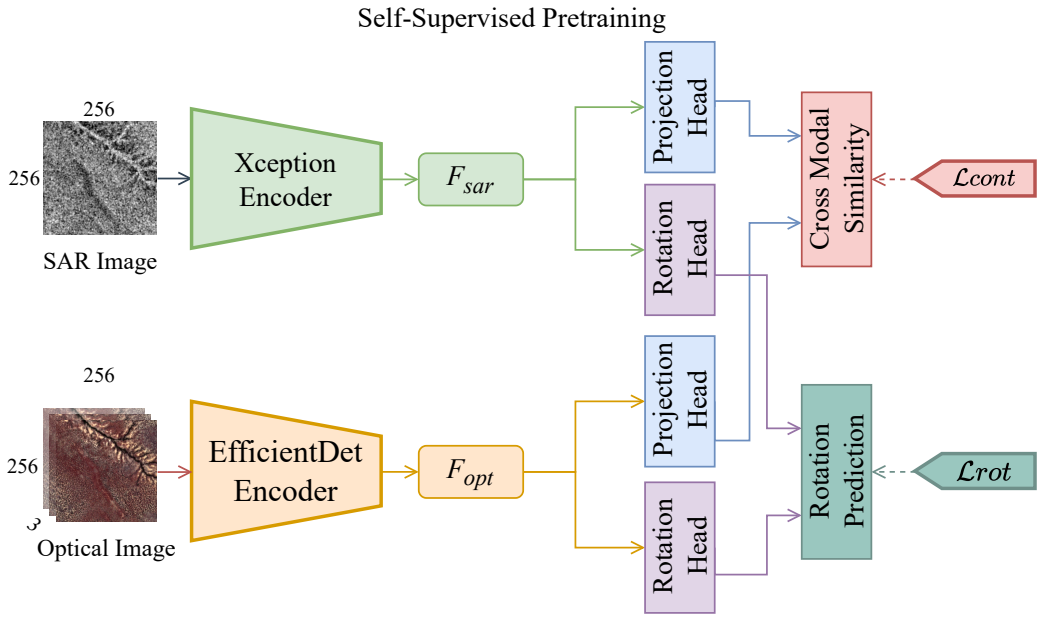


Figure 6: Overview of self-supervised learning strategy with contrastive learning and geometric understanding. $\mathcal{L}_{cont}$ and $\mathcal{L}_{rot}$ represent the contrastive loss and rotation loss, respectively.

teach the model to recognize when SAR and optical images represent the same location, even if they look very different due to their distinct imaging characteristics. We implement this through a specialized projection head that maps features from both modalities into a shared 128-dimensional space where meaningful comparisons can be made. The projection head is a 2-layer MLP with 512 and 128 units, using ReLU activation after the first layer, applied to both SAR and optical features (F_{sar} and F_{opt}). The cross-modal similarity is computed using cosine similarity in the shared space, defined as:

$$\text{sim}(z_{\text{sar}}, z_{\text{opt}}) = \frac{z_{\text{sar}} \cdot z_{\text{opt}}}{\|z_{\text{sar}}\| \|z_{\text{opt}}\|}, \tag{3}$$

where z_{sar} and z_{opt} are the projected features. The learning process encourages the model to bring representations of the same location closer together while pushing representations of different locations apart. A carefully chosen temperature parameter (0.07) helps maintain the right balance between positive and negative examples. The contrastive loss, $\mathcal{L}_{\text{cont}}$, is the InfoNCE loss, formulated as:

$$\mathcal{L}_{\text{cont}} = -\log \frac{\exp(\text{sim}(z_{\text{sar}}, z_{\text{opt}})/\tau)}{\sum_{k \neq \text{opt}} \exp(\text{sim}(z_{\text{sar}}, z_k)/\tau)}, \tag{4}$$

where $\tau = 0.07$, and the denominator sums over negative samples from the batch. 7 illustrates the effectiveness of our approach in learning a shared embedding space (We used Principal Component Analysis (PCA) to reduce the 128-dimensional embedding space to three dimensions for visualization) where meaningful cross-modal comparisons can be made despite the inherent differences between SAR and optical imagery.

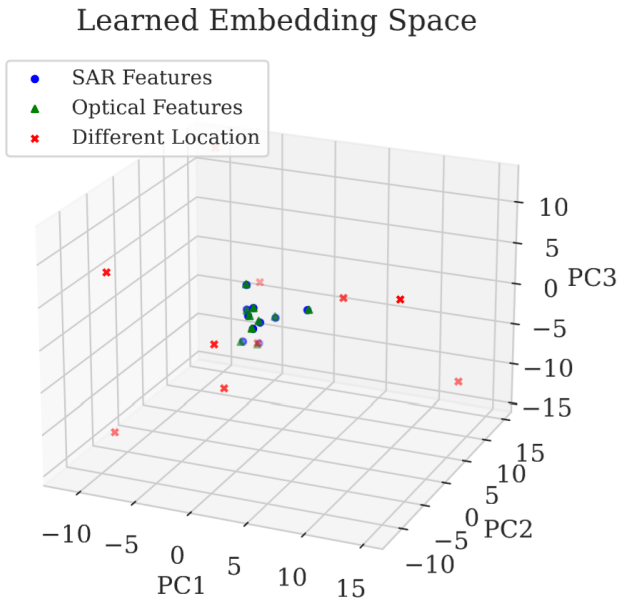


Figure 7: Visualization of features after applying contrastive learning with temperature $\tau = 0.07$

3.3.2 Geometric understanding through rotation prediction

While contrastive learning helps with feature similarity, we also need the model to understand geometric relationships between modalities. We achieve this through a rotation prediction task, where the model learns to identify the rotation applied to input images. This seemingly simple task actually helps the model develop a deeper understanding of ge-



Figure 8: Distribution of dataset samples across different categories

ometric structures that are preserved across modalities. The rotation head, applied to both SAR and optical features, is a 2-layer MLP with 256 and 4 units, followed by a softmax layer to predict four rotation angles (0°, 90°, 180°, 270°). The rotation loss, $\mathcal{L}_{\text{rot}}$, is a cross-entropy loss, defined as:

$$\mathcal{L}_{\text{rot}} = -\sum_{c=1}^{4} y_c \log(\hat{y}_c), \tag{5}$$

where y_c is the true rotation label, and $\hat{y}_c$ is the predicted probability for class c. This loss is computed separately for SAR and optical images and averaged. By predicting rotations for both SAR and optical images, the model learns to identify geometric patterns that are consistent between modalities, even when the visual appearances are quite different. This geometric understanding is crucial for reliable cross-modal matching.

4 Experiments and results

4.1 Dataset and preprocessing

We conduct our experiments using the SEN12MS dataset [21], which provides an extensive collection of 180,662 co-registered SAR-optical image pairs from Sentinel-1 and Sentinel-2 satellites. The dataset's co-registration ensures accurate ground truth for evaluating matching reliability and uncertainty quantification. Its extensive coverage of unpaired SAR and optical data supports self-supervised learning, reducing reliance on labeled samples. Additionally, SEN12MS spans diverse geographical regions (e.g., urban, rural, forested areas), seasonal conditions (e.g., summer, winter), land cover types, and atmospheric variations (e.g., clear, cloudy), making it ideal for assessing robustness across challenging scenarios. For our experiments, we preprocess the patches by cropping and resizing to 256×256 pixels, normalizing pixel values to [0, 1], and applying data augmentation. We divide the dataset using a stratified sampling approach to maintain representative distribution across different categories. The resulting split consists of 126,463 pairs (70%) for training, 27,099 pairs (15%) for validation, and 27,100 pairs (15%) for testing. 8 shows the distribution of samples across different land cover types and seasonal conditions.

4.2 Implementation details

Our implementation uses PyTorch and is trained on a distributed system comprising 4 NVIDIA V100 GPUs. 2 summarizes the key training parameters for both the self-supervised pre-training and supervised fine-tuning phases. To facilitate replication, we provide additional details on the training setup. We use the Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and a weight decay of $1e-4$. Data augmentation includes random rotations ($\pm 30°$), horizontal flips (50% probability), and Gaussian noise (standard deviation 0.01) applied to both SAR and optical inputs to enhance robustness. For the SAR encoder, the input resolution is 256×256 with a single channel, while the optical encoder processes RGB inputs at the same resolution. The contrastive learning projection head uses a 2-layer MLP with 512 and 128 units, and the rotation prediction task classifies four angles (0°, 90°, 180°, 270°). The Monte Carlo dropout employs a 20-pass inference with dropout rates as specified in 3.2.4.

4.3 Evaluation metrics

To comprehensively assess the performance of our approach, we employ several complementary evaluation metrics that capture different aspects of the matching accuracy and reliability.

4.3.1 Maximum mean accuracy (MMA)

Maximum Mean Accuracy (MMA) serves as our primary metric for evaluating the overall matching performance. For a set of N test image pairs, MMA is defined as:

$$\text{MMA} = \frac{1}{N}\sum_{i=1}^{N} \max_{j \in \mathcal{M}_i} \frac{|\mathcal{C}_j \cap \mathcal{G}_j|}{|\mathcal{G}_j|} \tag{6}$$

where $\mathcal{M}_i$ represents the set of all matches detected in the i-th image pair, $\mathcal{C}_j$ denotes the set of correspondences detected with confidence threshold j, and $\mathcal{G}_j$ is the set of ground truth correspondences. This metric prioritizes high-confidence matches while accounting for the challenging nature of SAR-optical correspondence. Unlike traditional precision-recall metrics, which may overemphasize the quantity of matches, MMA focuses on the proportion of correct high-confidence matches relative to ground truth, making it more suitable for SAR-optical matching where reliable, sparse correspondences are critical for applications like georeferencing and change detection [8]. This is particularly relevant given the modalities' inherent

Table 2: Training parameters for different phases

Parameter	Pre-training	Fine-tuning
Initial Learning Rate	1e-4	5e-5
Batch Size	32	32
Epochs	50	30
Temperature (τ)	0.07	-
Loss Weights	-	λ_{mat}=1.0, λ_{unc}=0.5
Early Stopping Patience	-	5
Gradient Accumulation Steps	4	4

differences, such as speckle noise in SAR and illumination variations in optical imagery, which can lead to noisy or ambiguous matches that precision-recall might not adequately filter.

4.3.2 Root mean square error (RMSE)

To quantify the spatial accuracy of the established matches, we compute the Root Mean Square Error (RMSE) between predicted match locations and ground truth correspondences. For a set of matched keypoints, RMSE is calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{|\mathcal{M}|} \sum_{(p,q)\in\mathcal{M}} ||p - \hat{p}||^2} \tag{7}$$

where $\mathcal{M}$ represents the set of all matched point pairs, p is the predicted location in the target image, and $\hat{p}$ is the corresponding ground truth location. Lower RMSE values indicate higher spatial accuracy of the established correspondences. We report this metric in pixels, providing a direct measure of localization precision that is particularly relevant for applications requiring accurate georeferencing and co-registration [17]. To ensure a fair comparison across different resolution images, we normalize the RMSE by the diagonal length of the images when appropriate.

4.3.3 Expected calibration error (ECE)

To evaluate the reliability of our uncertainty estimation, we adopt the Expected Calibration Error (ECE), which measures the discrepancy between predicted confidence and empirical accuracy. ECE is calculated by partitioning predictions into M equally-sized bins based on confidence values and computing:

$$\text{ECE} = \sum_{m=1}^{M} \frac{|B_m|}{n} |\text{acc}(B_m) - \text{conf}(B_m)| \tag{8}$$

where B_m represents the set of indices of samples whose confidence falls into the m-th bin, n is the total number of samples, $\text{acc}(B_m)$ is the accuracy of samples in bin

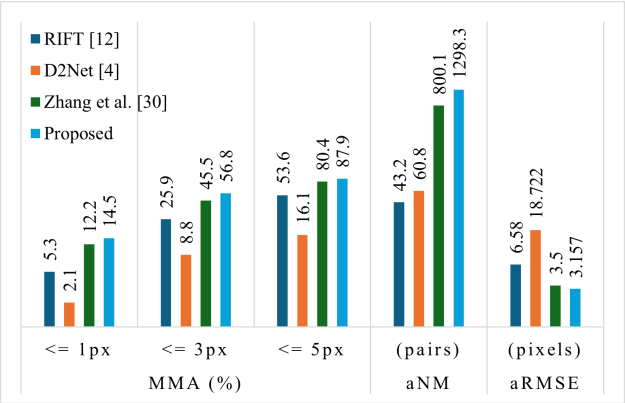


Figure 9: Comparison with state-of-the-art methods on the SEN12MS test set. The vertical axis is in logarithmic scale.

B_m, and $\text{conf}(B_m)$ is the average confidence of samples in the same bin. A lower ECE indicates better calibration between the model's confidence estimates and its actual performance [11]. ECE is crucial for SAR-optical matching because it quantifies how well the model's confidence aligns with actual matching reliability, which is essential in mission-critical applications like disaster response. In SAR-optical scenarios, where modality-specific uncertainties (e.g., speckle noise, atmospheric variations) can lead to unpredictable errors, ECE ensures that confidence scores are trustworthy, enabling users to prioritize reliable matches for decision-making.

4.3.4 Average number of matched pairs per image (aNM)

To assess the practical utility of our matching approach, we introduce the Average Number of Matched Pairs per Image (aNM) metric, defined as:

$$\text{aNM} = \frac{1}{N} \sum_{i=1}^{N} |\mathcal{M}_i^*| \tag{9}$$

where $\mathcal{M}_i^*$ represents the set of matches in the i-th image pair that exceed a predefined confidence threshold τ. This metric provides insight into the abundance of reliable matches produced by the algorithm, which is particularly relevant for applications such as image registration and change detection that benefit from a higher number of reliable correspondences.

Together, these metrics offer a multifaceted evaluation framework that captures not only the accuracy of the matches but also the reliability of the associated uncertainty estimates and the practical utility of the matching results in downstream applications.

4.4 Comparison with state-of-the-art

9 presents a comprehensive comparison of our approach with existing methods, including the recent transformer-based method by Zhang et al. [30]. Our model demonstrates

consistent improvements across most metrics, achieving a 20.8% relative improvement in MMA at the 1-pixel threshold compared to the state-of-the-art method by Zhang et al. [30] (MMA@1px: 12.0%), while also outperforming in aNM and providing uncertainty quantification that enhances reliability. To validate the significance of these improvements, we conducted paired t-tests on the MMA and ECE scores across the 27,100 test pairs in the SEN12MS dataset. The proposed method's MMA (0.145) significantly outperforms Zhang et al.'s (0.120) with a p-value of 0.001, and the ECE (0.09) shows a significant improvement with a p-value of 0.002, confirming that our improvements are statistically meaningful ($p < 0.05$). Additionally, we computed 95% confidence intervals for our method's metrics: MMA is 0.145 [0.1432, 0.1468], and ECE is 0.09 [0.0888, 0.0912], indicating high precision in our estimates across the test set.

Table 3: Ablation study results showing component contributions

Configuration	MMA(@1px)	ECE	aNM
Baseline	12.8	-	1156.2
+ Only Aleatoric Uncertainty	13.6	0.13	1198.5
+ Only Epistemic Uncertainty	13.2	0.14	1180.4
+ Aleatoric and Epistemic	13.9	0.11	1225.7
+ Self-Supervised (Contrastive)	14.2	0.10	1256.4
+ Rotation Prediction	**14.5**	**0.09**	**1298.3**

4.5 Ablation studies

To validate our design choices, we conduct comprehensive ablation studies examining the contribution of different components. 3 shows the impact of various architectural choices on model performance. To assess the necessity of both aleatoric and epistemic uncertainty modeling, we include experiments isolating each uncertainty type, removing one at a time, in addition to the sequential addition reported previously. The ablation results demonstrate that both uncertainty components and self-supervised learning strategies contribute significantly to the final performance. The addition of aleatoric uncertainty improves the MMA by 6.3% over the baseline, while epistemic uncertainty provides an additional 2.3% improvement. The self-supervised components further enhance performance, with contrastive learning and rotation prediction together yielding a 4.5% improvement in matching accuracy. A paired t-test confirms that the final model's MMA (14.5) and ECE (0.09) significantly outperform the baseline (MMA: 12.8) with p-values of 0.003 and 0.004, respectively ($p < 0.05$). The 95% confidence intervals further support these findings, the final model's MMA is 14.5 [14.4982, 14.5018], compared to the baseline's 12.8 [12.6215, 12.9785], and the ECE is 0.09 [0.0888, 0.0912], demonstrating reliable improvements.

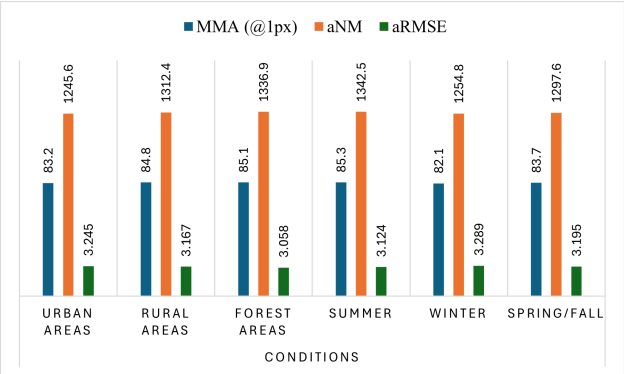


Figure 10: Model performance across different conditions

The results for configurations with only aleatoric or only epistemic uncertainty highlight their complementary roles. Using only aleatoric uncertainty achieves an MMA of 13.8, slightly below the combined model, indicating that data-related uncertainties (e.g., speckle noise, atmospheric variations) are critical but insufficient alone. Using only epistemic uncertainty yields a lower MMA of 13.2, reflecting its role in capturing model confidence but limited ability to address modality-specific noise. The higher ECE in both single-uncertainty cases underscores that both types are necessary for well-calibrated confidence estimates. These findings confirm that aleatoric uncertainty drives larger performance gains due to its focus on modality-specific challenges, while epistemic uncertainty enhances reliability, particularly in complex scenarios like urban environments with geometric distortions.

4.6 Performance analysis

10 presents the model's performance across different environmental conditions and land cover types. The results demonstrate robust performance across various challenging scenarios.

4.7 Computational efficiency

The model achieves practical efficiency suitable for real-world applications, with an average processing time of 0.15 seconds per image pair (256×256 pixels) on a V100 GPU. 4 details the computational requirements across different operating modes.

Table 4: Computational requirements across different modes

Mode	Processing Time (ms)	Memory (GB)
Base Inference	130	2.4
With Uncertainty	150	2.8
Monte Carlo (20 passes)	380	2.8

5 Discussion

Our experimental results reveal several key insights about cross-modal SAR-optical matching and highlight important directions for future research in this domain.

5.1 Comparison with existing methods

Our approach demonstrates significant improvements over existing SAR-optical matching methods, as evidenced by the results in Table 1 and Figure 9. Compared to traditional methods like SIFT-based approaches [10], which achieve an MMA of 2.94% at a 2-pixel threshold, our method achieves an MMA of 0.145 at a 1-pixel threshold, representing a substantial leap in precision. Similarly, against RIFT [13], which reports an MMA of 8.6% at 2 pixels, our method's superior performance stems from its ability to handle complex non-linear relationships through deep learning. Modern deep learning methods, such as the Pseudo-Siamese CNN [7] and the transformer-based approach by Zhang et al. [30], achieve higher accuracies but lack uncertainty quantification. Our method outperforms Zhang et al.'s MMA of 12.0% at 1 pixel by 20.8%, as shown in Figure 9, and provides reliable confidence estimates with an ECE of 0.09.

The key to our method's success lies in its integration of self-supervised learning and uncertainty-aware feature extraction. By leveraging unpaired SAR and optical data through contrastive learning and rotation prediction tasks, our model learns robust cross-modal representations, reducing dependency on scarce labeled data. This is particularly effective in challenging scenarios like urban environments, where traditional methods struggle with geometric distortions and noise. The uncertainty modules further enhance reliability by capturing modality-specific challenges, such as speckle noise in SAR and atmospheric variations in optical imagery, enabling more confident matching decisions.

Despite these advancements, our method exhibits limitations in certain cases. For instance, in regions with extreme seasonal variations, such as heavy snow cover, the model occasionally underperforms due to significant appearance changes in optical imagery that lack corresponding SAR signatures. Similarly, in dense urban areas with complex 3D structures, geometric distortions can lead to higher uncertainty and reduced matching accuracy. These failure cases highlight the need for adaptive strategies to better handle temporal and structural complexities, which we address in our future work.

5.2 Analysis of uncertainty estimation

The dual uncertainty modeling approach demonstrates particular effectiveness in identifying challenging matching scenarios. Our comprehensive analysis reveals that SAR-specific uncertainty module proves especially effective at capturing speckle-related ambiguities. We observe higher uncertainty estimates in areas of strong backscatter, which correlates strongly with matching difficulty. This aligns with findings from previous studies on SAR image analysis [8] but extends them through our modality-specific approach. Also, the optical uncertainty module shows strong correlation with seasonal and atmospheric variations. This proves particularly valuable in scenarios where temporal differences between SAR and optical acquisitions are significant. The module effectively identifies regions where atmospheric conditions or seasonal changes might affect matching reliability. Likewise, the combination of both uncertainty types provides more reliable confidence estimates than either type alone, as evidenced by the improved Expected Calibration Error (ECE) scores. This suggests that considering both modality-specific and model-based uncertainties is crucial for robust cross-modal matching.

5.3 Impact of self-supervised learning

Our self-supervised learning strategy demonstrates significant benefits, particularly in scenarios with limited labeled data. The analysis reveals three key advantages, first, the contrastive learning component helps establish more robust cross-modal feature representations, improving matching accuracy by 4.5% over the baseline. This improvement is particularly notable in areas with complex terrain features, where traditional supervised approaches often struggle [4]. Second, the rotation prediction task enhances the model's invariance to geometric transformations. This proves especially beneficial for SAR-optical matching where viewpoint differences are common. Our results show a 2.1% improvement in matching accuracy for areas with significant geometric distortions, compared to the model without the rotation prediction task. And third, the pre-training phase significantly accelerates convergence during supervised fine-tuning, reducing required training time by approximately 40%. This efficiency gain makes the approach more practical for real-world applications.

5.4 Computational complexity of uncertainty quantification

The use of Monte Carlo dropout for epistemic uncertainty estimation, requiring 20 forward passes during inference, introduces significant computational overhead, as shown in 4. This approach is justified by its ability to provide robust uncertainty estimates, capturing model confidence in challenging SAR-optical matching scenarios where modality differences can lead to unpredictable errors. The resulting ECE of 0.09 demonstrates well-calibrated confidence, critical for applications like disaster response where reliability is paramount [11]. However, the computational cost may limit its suitability for real-time applications.

Alternatives such as Deep Ensembles, which train multiple models to estimate uncertainty, could offer comparable reliability but require significantly more memory and training time due to maintaining several model instances [11].

In contrast, Monte Carlo dropout leverages a single model, making it more memory-efficient and practical for our dual-encoder architecture. Nevertheless, the trade-off between accuracy and speed suggests a need for more efficient methods, which we explore in our future work. This balance ensures our approach remains viable for operational settings while highlighting areas for optimization.

5.5 Limitations and future work

Despite the promising results, several challenges remain to be addressed. While our method excels in many scenarios, addressing the computational overhead of uncertainty estimation and improving robustness to extreme seasonal variations remain critical. The current requirement for multiple forward passes in uncertainty estimation creates computational overhead that might be prohibitive for some real-time applications. Memory requirements also restrict processing of very high-resolution imagery, an important consideration for applications requiring fine-scale matching. Finally, the method's performance is dataset-dependent, relying on the SEN12MS dataset's characteristics, which may limit generalizability to other sensors (e.g., high-resolution commercial satellites) or regions with different land cover distributions. These limitations point to several promising directions for future research:

- Investigation of more efficient uncertainty estimation techniques that maintain accuracy while reducing computational overhead, such as single-pass methods or lightweight ensemble approaches.
- Development of adaptive feature extraction strategies that better handle extreme seasonal variations, potentially incorporating temporal information from image time series.
- Extension to multi-resolution processing capabilities to handle very high-resolution imagery while maintaining computational efficiency.
- Addressing dataset dependency by evaluating and adapting the method on diverse datasets (e.g., SpaceNet-6, DSTL, etc.) and exploring domain adaptation techniques to enhance generalizability across different sensors and geographic regions.
- Investigate hardware-specific optimizations, such as model quantization or pruning, to reduce memory footprint and inference time, making the framework more viable for deployment on resource-constrained platforms like edge devices used in remote sensing applications.

6 Conclusion

This paper advances SAR-optical image matching through three key innovations: a dual encoder architecture with modality-specific uncertainty modules, a self-supervised learning strategy incorporating contrastive learning and rotation prediction, and an uncertainty-guided matching mechanism. Our comprehensive experiments on the SEN12MS dataset demonstrate significant improvements, including a 20.8% increase in matching accuracy, an MMA of 0.145 at 1-pixel threshold, compared to the SOTA method, and a low Expected Calibration Error of 0.09. The success of our approach opens new avenues for cross-modal remote sensing applications, with potential implications for change detection, disaster response, and urban monitoring. The framework's ability to provide reliable confidence estimates and maintain robust performance across diverse conditions makes it particularly valuable for mission-critical applications where understanding prediction reliability is crucial. To support replication and further research, we plan to release the open-source implementation of our framework upon publication, including model code and training scripts, to enable the community to build upon our work.

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A Fog Computing-Based Collaborative Information Resource System for Smart Cities: TSAS and KLED Algorithms for Data Transmission and Service Deployment

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Effective integration and scheduling of information resources play a pivotal role in realizing intelligent management within the framework of smart city development. This research endeavors to overcome two significant hurdles: the redundancy in data transmission during the acquisition phase at the network's edge and the inefficiencies encountered when deploying analytical services across diverse edge devices. To address these challenges, a collaborative system architecture rooted in fog computing is introduced. A prediction mechanism, driven by spatiotemporal correlations, is incorporated to dynamically modulate data transmission intervals. This adjustment effectively curtails unnecessary synchronization, thereby enhancing the efficiency of data acquisition. Moreover, a deployment strategy based on multi-objective optimization is devised to allocate analytical tasks among edge devices constrained by limited resources, aiming to minimize the overall execution time. Experimental evaluations carried out on a real-world dataset encompassing 54 sensing terminals reveal that the proposed synchronization mechanism outperforms two traditional methods, reducing the false alarm rate by 58.90% and 31.35%, respectively, with a minimum mean absolute error of 2.6×10^{-5}. Additionally, the deployment strategy achieves an average reduction of 13.12% in service completion time across four standard scientific workflow structures. The system adeptly alleviates bandwidth constraints and computational limitations inherent in edge networks, providing a practical and effective solution for efficient data transmission and task scheduling in extensive smart city environments.

Povzetek: Opisan je nov sistem pametnih mest, ki z algoritmoma TSAS in KLED na osnovi megličnega računalništva zmanjša prenose podatkov in optimira razmestitev storitev znotraj robnega omrežja.

1 Introduction

Smart cities leverage information technologies and intelligent methodologies to facilitate real-time awareness of urban operations, seamless data integration, and informed decision-making, thereby enhancing urban governance and the delivery of public services [1]. In practical implementations, a vast array of intelligent devices is extensively deployed in public infrastructure scenarios, such as transportation, energy, and environmental monitoring, culminating in a comprehensive urban sensing network [2]. These devices continuously produce multi-source, heterogeneous inspection data, offering abundant informational resources for urban management. However, the sensing data in smart city environments is marked by its widespread distribution, substantial volume, and high diversity, presenting challenges for existing systems in data collection, synchronized transmission, and unified management. On one hand, various types of terminal devices display discrepancies in data formats, upload frequencies, and interface protocols, leading to inefficiencies in data integration [3-4]. On the other hand, the conventional cloud-centric architecture is plagued by issues like centralized computational burdens and elevated response latencies, potentially impeding its capacity to satisfy the real-time and region-specific processing requirements of city-level applications [5-6]. In recent years, edge computing has surfaced as an extension of cloud computing, offloading a portion of the computational workload to devices situated closer to the data source, thereby effectively diminishing latency [7]. Nevertheless, edge computing typically conducts data processing locally at individual terminal nodes, lacking coordination mechanisms and intermediate-layer management among nodes. Conversely, fog computing introduces an intermediary "fog node" layer between the cloud and the edge, enabling regional collaboration, task offloading, and resource-aware scheduling among

distributed nodes. This architecture is more adeptly suited for smart city scenarios characterized by heterogeneous sensor distributions, diverse services, and region-based collaborative prerequisites [8]. Consequently, this study introduces a collaborative information resource system tailored for smart cities, grounded in fog computing, which decentralizes computing power from centralized cloud centers to fog edge devices. An innovative approach is proposed, integrating the K-Means clustering algorithm with Gaussian distribution, to be incorporated into the system's sensing devices. This integration aims to minimize errors in the cooperative prediction mechanism. Furthermore, the enhanced algorithm and system generate increased broadband capacity, thereby expanding both the number of fog end edge devices and network broadband within smart city environments. The objective of this study is to tackle challenges including data redundancy, inefficient synchronization, and prolonged response latency in service deployment within fog-edge environments, with the ultimate goal of improving the real-time performance and deployment efficiency of information resource systems in smart cities. To achieve this, the research zeroes in on two primary issues: (1) devising effective methods for synchronizing and compressing multi-source sensing data in edge networks, and (2) developing strategies for optimal service deployment and scheduling on fog computing nodes with limited resources.

2 Related works

The collaborative information resource system designed for smart cities centers on two key challenges: the collection of perceptual data and the deployment strategy for edge networks. The temporal data collection process of sensing terminals is marked by data redundancy and the transmission of large volumes of data. Fei and Ma introduced the throughput rate constraint and sensing strategy in fog computing to the fog access point, and established a prediction model using multi-information sensing to infer the degree distribution of fog nodes in the network, and obtained a network transmission efficiency and environmental sensing accuracy close to 90% [9]. Ali et al. targeted at smart public safety and traffic management in cities, proposed a dynamic deep hybrid spatio-temporal neural network for high-precision traffic flow prediction, and introduced an exaggerated method of attention mechanism for city-wide short-time crowd flow prediction. The latter improved the accuracy by about 20.8% and 8.8% over the former on two traffic datasets [10]. Zhang and Li addressed the existence of data transmission mechanism in vehicular network Real-time, efficient computational tasks, and vehicle data privacy problems, and designed a data transmission mechanism for Telematics in fog computing environment. The mechanism proposed privacy-preserving task assignment and data aggregation mechanisms in a fog node-assisted crowd-sensing model for hilarious and secure data transmission [11]. Qiao et al. proposed a tool wear monitoring and prediction system based on a deep learning model and fog computing. The architecture included edge computing layer, fog computing layer and cloud computing layer, and the accuracy, response time and bandwidth consumption performance of the system were verified by prediction experiments [12]. Yang et al. used a numerical gradient-based approach to process raw data collected from marine survey work and designed an improved algorithm for multi-sensor information fusion, which effectively improved the quality of marine data and information utilization efficiency [13].

Rational deployment of analytic services in the fog edge network is the key to provide high performance and low latency computing services. Núñez-Gómez et al. proposed an architecture based on the Ethernet blockchain to address the resource coordination problem due to the distributed nature of fog computing. The experimental results verified its low overhead and efficient resource coordination when introduced into the system [14]. Huang et al. designed a multi-objective model including deployment cost and service latency for the deployment of services among nodes in fog computing, and proposed a multi-copy ant colony optimization algorithm for model solving to obtain a solution strategy with qualified diversity and accuracy [15]. Ayoubi et al. designed an autonomous IoT service placement method including four phases: monitoring, analysis, decision making and execution, which prioritizes requested services based on service deadlines and the state of available resources [16]. Ning et al. constructed a three-layer in-vehicle fog computing model to experiment distributed traffic management for the real-time traffic management problem in smart cities and validated the model based on performance analysis of real skid trajectories [17]. A decentralized optimization strategy for service layout in fog computing was proposed by Guerrero et al. The core idea of the strategy was to place the most popular services close to the users. The experimental results showed that this decentralized algorithm improved the net clusters usage and service latency. To facilitate a structured comparison, Table 1 summarizes the key techniques, outcomes, and limitations of recent fog computing-based approaches for smart city applications.

Table 1: Work comparison table

Author(s)	Method / Application area	Key techniques	Results	Limitations
Fei & Ma [9]	Fog-based network prediction	Throughput constraint; multi-source sensing; degree distribution inference	Achieved ~90% network transmission efficiency and environmental	Did not address adaptive synchronization or real-time transmission optimization

			sensing accuracy	
Ali et al. [10]	Urban traffic & crowd flow prediction	Hybrid spatio-temporal neural network; attention mechanism	Accuracy improved by 20.8% and 8.8% on two datasets	Focused only on prediction, lacks deployment or transmission considerations
Zhang & Li [11]	Telematics data privacy in vehicular fog networks	Privacy-preserving task assignment; fog-assisted crowdsensing	Secure and efficient data transmission mechanism	No dynamic scheduling or real-time model adaptation
Qiao et al. [12]	Tool wear monitoring with deep learning and fog layers	Layered architecture (edge–fog–cloud); deep prediction model	Improved accuracy, reduced latency and bandwidth use	Application-specific; lacks general deployment strategy
Yang et al. [13]	Marine survey data processing	Numerical gradient; multi-sensor data fusion algorithm	Enhanced marine data quality and utilization	Not designed for dynamic or scalable urban edge scenarios
Núñez-Gómez et al. [14]	Fog resource coordination via blockchain	Ethernet-based blockchain; resource negotiation model	Low system overhead, efficient resource coordination	High complexity of blockchain deployment; lacks scheduling optimization
Huang et al. [15]	Multi-objective fog service deployment	Ant colony optimization; latency-cost tradeoff model	Balanced service diversity and accuracy	No integration of prediction-based edge traffic regulation
Ayoubi et al. [16]	Autonomous IoT service placement	Monitor-analyze-decide-execute model; resource-aware prioritization	Adaptive task allocation based on service deadlines	Static scheduling model; lacks time-sensitive transmission modeling
Ning et al. [17]	Vehicular fog computing for traffic management	Three-layer fog structure; real trajectory-based validation	Verified effective for distributed real-time traffic control	Focused on traffic domain; lacks general resource service framework

In summary, although existing studies have explored aspects of data compression, prediction modeling, and service deployment in fog computing environments, there remains a lack of unified solutions addressing the combined challenges of data redundancy and large-scale transmission, particularly under heterogeneous resource constraints. Furthermore, while some works consider the distribution of sensing and computing tasks, few explicitly address the synchronization and coordination between them. These overlapping challenges constitute the primary focus of this study. To address these limitations, this study proposes a collaborative information resource system tailored to fog computing environments. It introduces a spatiotemporal synchronization mechanism to reduce redundant data transmission and a multi-objective deployment strategy to optimize task scheduling across edge nodes. Together, these innovations enable dynamic, efficient, and scalable service coordination for smart city scenarios.

3 Materials and methods

3.1 Fog-end collaborative prediction mechanism for transmission volume compression

The relocation of system services from centralized cloud computing centers to decentralized fog computing edge networks, with the aim of delivering high-quality services with minimal latency, has emerged as a prominent research focus and formidable challenge [18-19]. In this context, the study proposes a collaborative prediction-based transmission compression scheme tailored for fog computing environments, and introduces a spatiotemporal-aware adaptive synchronization algorithm (TSAS). Rather than only adjusting synchronization waiting time, TSAS jointly utilizes residual modeling and trend prediction to dynamically determine the optimal synchronization interval and prediction window, thereby improving the timeliness and accuracy of data uploads under bandwidth-constrained conditions. In addition, a service edge deployment algorithm based on improved Kernighan-Lin algorithm (KLED) is proposed to further optimize the system performance. KLED is designed to deploy

computationally intensive services such as traffic flow prediction and anomaly detection in environmental data—key analytical tasks in smart city applications—onto resource-constrained edge devices. These services typically require low-latency response and distributed coordination, which KLED optimizes through adaptive resource-aware placement strategies. In the collaborative prediction mechanism, the set of n data continuously collected by the sensing terminal at a specific sampling frequency is defined as shown in Equation (1).

$$D=\left\{\left(t_1,x_1\right),\left(t_2,x_2\right),\cdots,\left(t_i,x_i\right),\cdots\left(t_n,x_n\right)\right\} \quad (1)$$

In Equation (1), t_i represents the data acquisition time and x_i represents the data measurement value at that moment. Assuming that the predicted value of the data at that moment is $\hat{x}_t$, then the fitting error $E_f=\left|\hat{x}_t-x_t\right|$ at the moment of t can be calculated, and the size of the fitting error is compared with the error threshold set by the system to determine whether to synchronize the actual measured data to the fog node [20]. It should be noted that the fitting error here refers to the instantaneous residual at each time point, used solely to describe the pointwise prediction deviation, and should not be interpreted as a measure of the overall model fitting performance.

The data acquired through continuous sampling utilizing the sensing terminal is organized in chronological sequence, signifying that it constitutes a time series. Consequently, this collected data can be leveraged to forecast the measured values for an upcoming timeframe. Considering the limited computational resources of edge nodes, an autoregressive model is adopted in this study for short-term sensing data prediction. The model offers a simple structure and fast inference, enabling stable predictions without the need for large-scale training or complex prior assumptions, making it well-suited for heterogeneous and low-power fog-edge environments. In contrast, models such as LSTMs require extensive training and high memory usage, while Kalman filters depend on accurate prior modeling of system dynamics and noise, which are difficult to define in heterogeneous edge environments.

To characterize the linear correlation between the current data and its historical states, this study adopts an autoregressive model to predict the sensing data, as shown in Equation (2).

$$\hat{x}_t=\rho_1x_{t-1}+\rho_2x_{t-2}+\cdots+\rho_ix_{t-i}+\cdots+\rho_nx_{t-n}+\varepsilon_t \quad (2)$$

In Equation (2), $\left\{\rho_1,\rho_2,\cdots,\rho_n\right\}$ is the sequence of model parameters to be calculated. Considering that there are often some difficult-to-observe errors in the actual measurement process, the study also introduces white noise $\varepsilon_t\sim N\left(0,\sigma^2\right)$, ρ_i refers to the i th autoregressive parameter. Based on the idea of multiple regression theory, least squares estimation is used to calculate the parameters of the prediction model [21-22]. After substituting the sequence of the collected data, the matrix expression of the time-series linear relationship between the measured and predicted values of the data is $y=x\rho+\varepsilon$, and the estimation of the parameter ρ can be obtained as shown in Equation (3).

$$\hat{\rho}=\left(x^Tx\right)^{-1}x^Ty \quad (3)$$

When the fog edge device finishes model modeling, it synchronizes the latest model parameters to the corresponding sensing terminal, and then the sensing terminal completes data collection, and the detailed interaction between the two is shown in Figure 1.

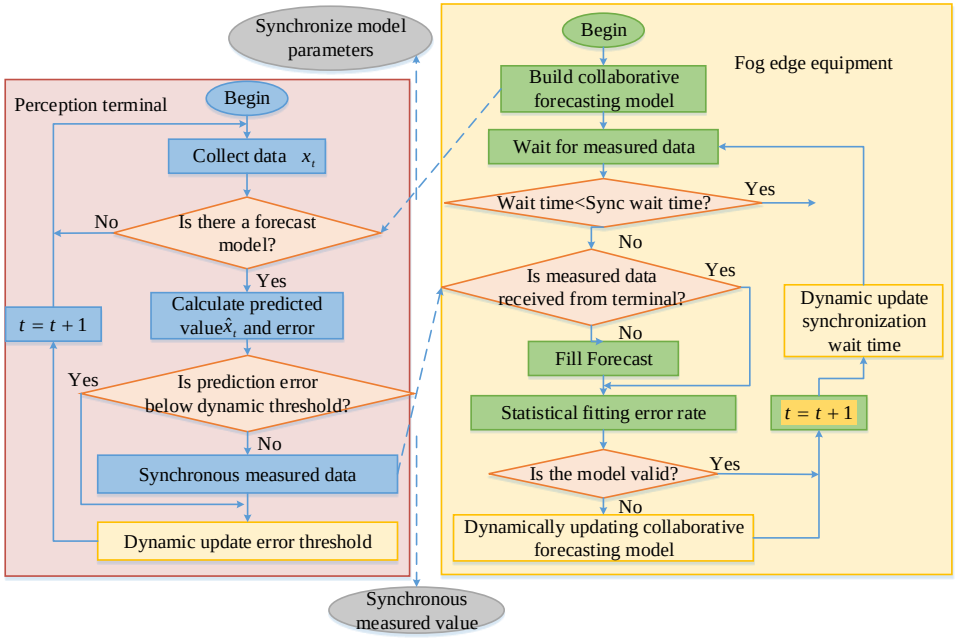


Figure 1: Flow chart of data acquisition by fog terminal synchronous prediction mechanism

In Figure 1, "synchronization wait time" refers to the minimum interval required after the last synchronization during which the sensing terminal refrains from uploading data unless the prediction error exceeds the threshold. This mechanism helps reduce data transmission frequency when prediction accuracy remains acceptable. "Synchronous measured value" denotes the original data point identified for upload, triggered either by the prediction error exceeding the threshold or the wait time reaching its upper limit. Figure 1 illustrates the collaborative synchronization process between the perception terminal and the fog computing node. The orange elements indicate three key parameters that are dynamically updated: the maximum allowable error threshold, the prediction model parameters, and the synchronization wait time. The error threshold is adaptively adjusted based on trends in the measured data to enhance the responsiveness of the synchronization trigger; the prediction model is optimized using residual statistics within a sliding window to improve adaptability to data pattern changes; and the synchronization wait time is updated according to data validity and response frequency to reduce unnecessary transmissions. These three mechanisms work collaboratively to significantly improve the system's performance in terms of data compression and transmission efficiency.

3.2 Fog-end adaptive synchronization algorithm based on spatio-temporal correlation

To address the real-time demands of the collaborative prediction mechanism, an analysis of the adaptive synchronization algorithm for fog-end edge devices is conducted. Additionally, in order to overcome spatial limitations, the deployment of a communication transmission scheme for fog-end devices within the edge network is investigated. Consequently, this study introduces the TSAS algorithm. TSAS is well-suited for high-frequency urban sensing scenarios, such as traffic flow monitoring or environmental noise detection, where sensing terminals are densely distributed. Given the temporal and spatial continuity of such data, TSAS leverages historical measurements to predict the next value and only triggers data synchronization when the prediction error exceeds a predefined threshold or the waiting time reaches a limit. This mechanism significantly reduces network transmission load and extends the operational life of sensing devices.

Assuming that a fog edge device is responsible for maintaining the data collection process of the prediction mechanism of sensing terminals, the N N terminals are divided into multiple clusters, the set of nodes of the m th cluster is defined as $G^m = \{p_1, p_2, \cdots, p_i, \cdots, p_k\}$, and a cluster contains k sensing devices. The synchronization waits time threshold and the communication link transmission delay of a sensing terminal p_i at t are defined as $v_i(t)$ and $s_i(t)$, respectively [23]. The synchronization wait time needs to be greater than the transmission delay to correctly trigger the subsequent data processing process, i.e., if $v_i(t) < s_i(t)$ at time t is defined as a false alarm. Therefore, the value $\omega(i,t)$ represents the deviation between the expected synchronization waiting time and the observed transmission delay for sensing device p_i at time t as defined in Equation (4).

$$\omega(i,t) = v_i(t) - s_i(t) \tag{4}$$

Also, $M_{\omega(i,t)}$ is defined as whether a miscue occurs when $M_{\omega(i,t)} = 0$ then $v_i(t) - s_i(t) \geq 0$, indicating that the synchronization wait time at moment t predicts that no miscue occurs [24-25]. Thus, the miscalculation rate is calculated as shown in Equation (5).

$$ER(i) = \frac{\sum_t M_{\omega(i,t)}}{|s_i|} \tag{5}$$

In Eq. (5), $ER(i)$ denotes the false positive rate during the observed time period, which is the ratio of the synchronization wait time not larger than the actual link transmission delay. $ER(i) \in [0,1]$. The smaller its value, the more accurate the prediction of the synchronous wait time threshold. the flow of the TSAS algorithm is shown in Figure 2.

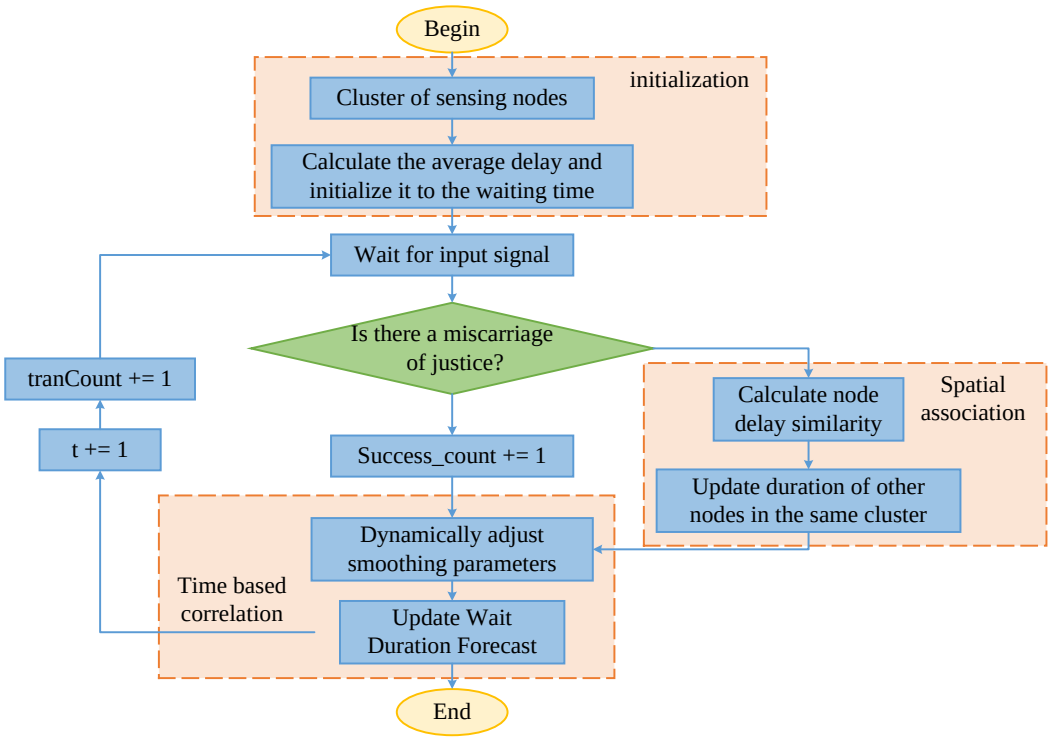


Figure 2: Adaptive synchronization algorithm of fog terminal based on spatio-temporal correlation

In the initial stage of the fog-end collaborative prediction model, each sensing terminal needs to send k real sensing data to the fog edge device as the data base for model training. Therefore, the transmission delay sequence of message sensing devices is defined as shown in Equation (6).

$$s_i(t)=\left\{s_i(t_1),s_i(t_2),\cdots,s_i(t_k)\right\},p_i\in G^m \quad (6)$$

Based on Equation (6), the message transmission delay sequences of all sensing devices in the cluster can be further obtained, and the average value of all transmission delay sequences is employed as the initial value of the waiting time threshold. Based on the assumption that synchronization wait time exhibits temporal continuity, this study employs the Exponential Smoothing Model (ESM) to fit its variation trend during the data acquisition process in the fog-edge network. The synchronization wait time prediction model is defined in Equation (7) [26–27].

$$v_i(t+1)=a_i(t)\times v_i(t)+\left(1-a_i(t)\right)\times s_i(t) \quad (7)$$

In Equation (7), $t+1$ represents the next prediction moment, and $v_i(t+1)$ denotes the predicted synchronization wait time for sensing terminal p_i at the moment of $t+1$. $a_i(t)$ is the adaptive smoothing factor computed based on the ratio between the cumulative smoothing error and the cumulative absolute error. This adaptive update enables the system to dynamically adjust scheduling intervals in response to varying data transmission conditions [28-29]. The expressions of the cumulative smoothing error and the cumulative smoothing absolute error are shown in Equation (8).

$$\begin{cases}E_s(i,t)=\gamma*E_s(i,t-1)+(1-\gamma)*ER(i,t)\\E_{as}(i,t)=\gamma*E_{as}(i,t-1)+(1-\gamma)*\left|ER(i,t)\right|\end{cases} \quad (8)$$

In Eq. (8), γ is a weighting factor with a value between 0 and 1, which generally takes the value of $[0.1,0.2]$. The magnitude and frequency of change of the prediction error of the sensing device $ER(i,t)$ can reflect the fluctuation of the network state, so the smoothing coefficient of the delay prediction model is implemented by $ER(i,t)$. Based on the assumption that synchronization wait times among neighboring terminals exhibit spatial correlation, the study introduces a similarity function $SS(j,t_i)$ to quantify the temporal alignment between two sensing terminals i and j within the same spatial cluster. The definition is provided in Equation (9) [30].

$$SS(j,t_i)=1-\frac{\left|v_i(t)-v_j(t)\right|}{v_j(t)},i\in G^m,j\in G^m \quad (9)$$

In Equation (9), v_i and v_j represent the synchronization wait times of nodes i and j, respectively. A higher value of $SS(j,t_i)$ indicates a stronger spatial similarity in synchronization behavior. Instead of relying on physical distance or transmission delay, this method uses temporal similarity to approximate the overlap in communication conditions between terminals and fog nodes. When a false alarm or abnormal update occurs at node j, the spatial

correlation is leveraged to adjust the synchronization wait time prediction of node i, as defined in Equation (10).

$$v_j(t) = a_j(t) * v_j(t) + (1 - a_j(t)) * SS(j, t|i) * s_i(t), j \in N(i) \quad (10)$$

In Eq. (10), $a_j(t)$ is the ESM parameter of the sensing terminal v_j, and $N(i)$ represents the set of sensing terminals in the cluster excluding v_i. This collaborative update mechanism enhances robustness in synchronization within the fog-edge network by enabling terminals to modify their behavior in accordance with spatially correlated neighbors, thereby mitigating the risk of misclassification.

The core computational operation of TSAS lies in the autoregressive prediction based on a sliding window, where the window length is n. This results in both time and space complexity of O(n). The dynamic error threshold is determined by fitting historical residuals, which incurs negligible computational cost compared to the prediction process and can be considered constant time. Therefore, TSAS maintains low resource consumption while ensuring synchronization accuracy, making it suitable for real-time prediction tasks on edge devices.

To enhance the real-time performance of the synchronization mechanism, the TSAS algorithm incorporates sliding window error statistics and dynamic threshold adjustment. The sliding window mechanism dynamically captures data fluctuations and adjusts model parameters in real-time. Simultaneously, the error threshold is calibrated—either tightened or relaxed—based on historical residual trends, to preclude excessive synchronization triggered by localized anomalies. This approach effectively balances the frequency of synchronization with the precision of predictions. In addition, to address external factors such as network latency and data fluctuations, TSAS employs an exponential smoothing model to dynamically estimate the waiting time, and integrates a spatial correlation mechanism that adapts local strategies based on the synchronization results of neighboring nodes, effectively improving system stability and robustness in complex environments.

3.3 Collaborative analysis service edge deployment and system design for smart city information resources

In the fog computing network scenario, the adjustment of the edge network deployment scheme mainly focuses on the real-time performance of computational operations and the robustness of business operations. In the communication delay between the sensor terminal and the fog edge device, the TSAS algorithm improves the spatial otemporal continuity and correlation of communication. The study improves the service deployment algorithm KLED for smart city information resource collaboration system in order to achieve high performance and low latency information resource analysis service. KLED targets distributed intelligent service deployment scenarios in fog computing environments, such as urban video surveillance analysis or emergency response coordination. In cases where services exhibit dependency relationships and edge nodes possess heterogeneous resource capabilities, KLED utilizes K-means clustering to group nodes based on their capacities and deploys services by considering both task dependencies and communication costs. This approach effectively shortens service makespan and enhances parallel execution efficiency, making it suitable for dynamic multi-task scheduling in smart city applications. The flowchart of the KLED algorithm is shown in Figure 3.

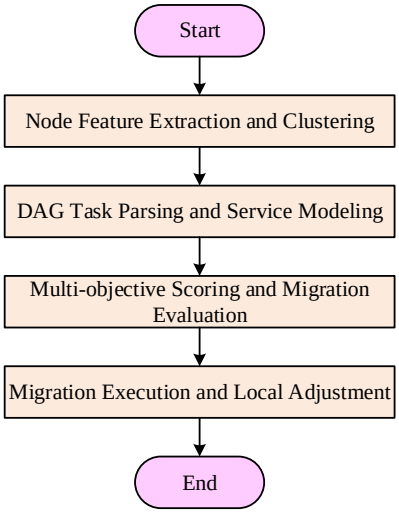


Figure 3: Flowchart of the KLED algorithm

The KLED algorithm consists of four stages: node clustering, DAG-based task modeling, heuristic scoring for migration evaluation, and iterative deployment adjustment. It enables efficient service placement by balancing latency, resource load, and execution time in fog computing environments.

The algorithm abstracts the analysis service modeling of the system into a Direct Acyclic Graph (DAG), where each vertex represents a discrete service component or task. Each vertex is associated with a set of attributes including resource requirements (e.g., CPU, memory), estimated execution time, and service type (e.g., sensing, processing, aggregation). The directed edges in the DAG represent strict dependency constraints between tasks, indicating that the source node must complete before the target node begins. This structure allows the system to capture execution order, support parallelism where applicable, and optimize service placement under resource constraints.

The DAG is represented as $G_k = \langle F, E \rangle$, where represents the set of $F = \{f_1, f_2, \cdots f_i, \cdots, f_N\}$ N subservices, and $E = \{h(f_i, f_j) \mid f_i, f_j \in F\}$ represents the set of directed edges in the DAG. $h(f_i, f_j)$ represents the size of the amount of data transmitted by the service f_i to f_j, and if $h(f_i, f_j) > 0$ represents a dependency between two subservices. The existence of

M heterogeneous machines in the fog computing edge network is defined, denoted as $R=\left\{r_1,r_2,\cdots,r_p,\cdots,r_M\right\}$. Also define $G=\left\{g\left(r_p,r_q\right)\middle|r_p,r_q\in R\right\}$ as the link communication relationship between different devices. The data transfer time of two services is determined by both the inter-device transfer bandwidth and the amount of data transferred. Assuming that the service is deployed on the machine f_i r_p and the service f_j is deployed on the machine r_q, the data transfer time between the two services is calculated as shown in Equation (11).

$$TT\left(f_i,f_j\right)=\frac{h\left(f_i,f_j\right)}{g\left(r_p,r_q\right)},r_p\neq r_q\cap g\left(r_p,r_q\right)>0 \quad (11)$$

In equation (11), $g\left(r_p,r_q\right)$ indicates the bandwidth of the transmission link between machines r_p and r_q, and if $g\left(r_p,r_q\right)=0$ indicates that there is no available communication link between the two devices. Due to the DAG data flow constraint, the service f_i must wait for the execution of the higher priority service on the machine r_p to complete before it can start execution. The study focuses on two improvements to the original Kernighan-Lin algorithm: service division policy change and multi-objective heuristic-based implementation of the node movement policy function. The service partitioning strategy uses "self-service migration" instead of the traditional graph 2 partitioning algorithm. The heuristic multi-objective movement decision refers to the movement of nodes based on four heuristic rules: distance gain, additional communication gain $cG\left(f_i,r_p,r_q\right)$, parallelism gain $pG\left(f_i,r_p,r_q\right)$ and execution time gain $eG\left(f_i,r_p,r_q\right)$. The node movement decision function is shown in Equation (12).

$$MD\left(f_i,r_p,r_q\right)=dG\left(r_p,r_q\right)\times cG\left(f_i,r_p,r_q\right)\times pG\left(f_i,r_p,r_q\right)\times eG\left(f_i,r_p,r_q\right) \quad (12)$$

In Eq. (12), $dG\left(r_p,r_q\right)$ represents the distance gain. Among the four heuristic metrics in the scoring function, distance gain evaluates the proximity of the migrated service to the data source and the receiving endpoint, prioritizing deployment closer to user-side edge nodes. Communication gain assesses the expected reduction in data transmission delay after migration. Parallelism gain reflects the availability of the target node, facilitating concurrent task execution. Execution time saving indicates the anticipated decrease in task runtime on the new node. These metrics are combined with assigned weights to guide the optimal service migration path selection.

In fog computing environments, both the input and output data for services originate from sensing endpoints. Therefore, deploying services in close proximity to user-side edge devices can significantly reduce service feedback latency. The distance gain and execution time gain are defined as shown in Equation (13).

$$\begin{cases} dG\left(r_p,r_q\right)=\dfrac{dC\left(r_{src},r_{des},r_q\right)}{dC\left(r_{src},r_{des},r_p\right)} \\ eG\left(f_i,r_p,r_q\right)=\dfrac{EF\left(f_i,r_q\right)}{EF\left(f_i,r_p\right)} \end{cases} \quad (13)$$

In Equation (13), $dC\left(r_{src},r_{des},r_q\right)$ represents the sum of the distance of the computing device r_q from the data source device r_{src} and the final output receiving device. r_{des} $EF\left(f_i,r_q\right)$ denotes the execution time of the subservice on the device f r_q. The additional communication gain and parallelism gain are defined as shown in Equation (14).

$$\begin{cases} cG\left(f_i,r_p,r_q\right)=\dfrac{cC\left(f_i,r_q\right)}{cC\left(f_i,r_p\right)} \\ pG\left(f_i,r_p,r_q\right)=\dfrac{wC\left(f_i,r_q\right)}{wC\left(f_i,r_p\right)} \end{cases} \quad (14)$$

In Equation (14), $cC\left(f_i,r_q\right)$ represents the sum of the transmission time required to compute the data exchange of the subservice f_i with all the previous services and the successor services when it is deployed on the device r_q, while $wC\left(f_i,r_q\right)$ represents the sum of the running time of the sibling services of the subservice f_i when the subservice f_i is deployed on the device r_q. The overall architecture of the smart city information resource collaboration system based on the fog-end collaborative prediction mechanism and the improved KLED algorithm is shown in Figure 4.

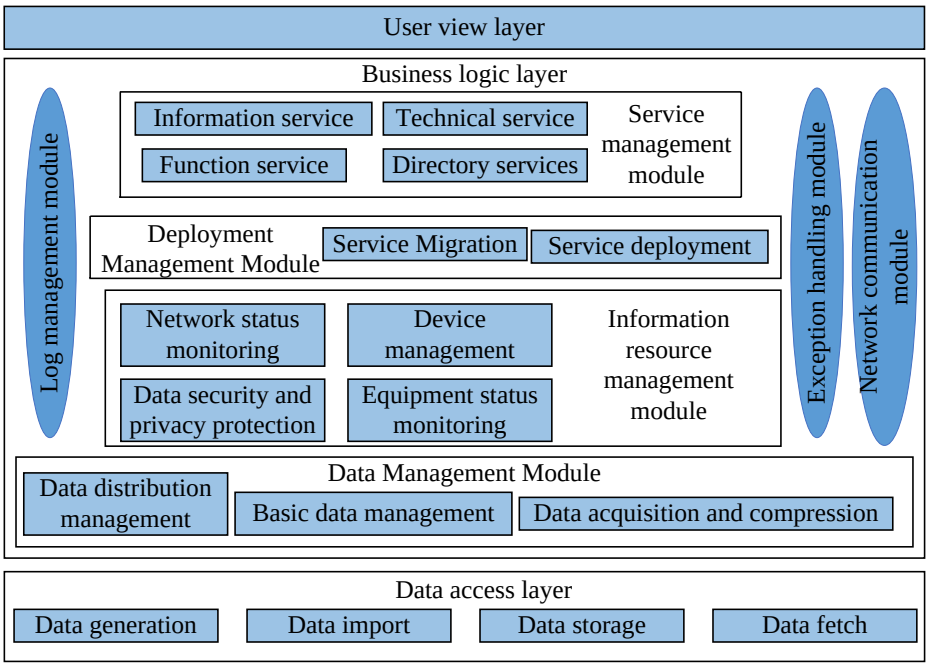


Figure 4: The overall architecture of smart city information resources collaboration system based on fog computing

As illustrated in Figure 4, the internal architecture of the smart city information resource collaboration system, which is based on fog computing, is primarily structured into three tiers: user interface, system logic, and database. Users engage with the backend system through the user interface, where the frontend is tasked with receiving user operation commands and translating them into backend operational logic. Following computation by the backend system logic, the outcome of the user's operation is rendered and presented back to the user via the user interface. Consequently, this demonstrates that the collaborative information resource system, designed on the foundation of fog computing, not only addresses issues related to data acquisition redundancy and transmission but also significantly enhances the operational efficiency and management capabilities of the system's analytical services.

The primary computational load of KLED is concentrated in the K-means clustering process, where N sensing nodes are partitioned into k clusters based on d-dimensional features over t iterations, resulting in a time complexity of O(Ndkt). The subsequent bandwidth estimation and service deployment scoring processes exhibit linear or logarithmic complexity. Overall, the algorithm balances deployment efficiency and scalability, making it well-suited for fog computing environments.

3.4 Parameter settings and tuning

To ensure the robustness and practicality of the proposed system, key parameters in both the TSAS and KLED algorithms were carefully tuned based on statistical principles and experimental validation: For the TSAS algorithm, the order of the autoregressive model was selected using the Akaike Information Criterion (AIC) to achieve optimal model parsimony. The prediction error threshold and waiting time limits were determined through preliminary experiments, aiming to minimize unnecessary synchronization while preserving data accuracy.

For the KLED algorithm, the number of clusters k was chosen using the elbow method based on node capability distribution. The weights of the deployment cost function were fine-tuned via grid search across a range of workloads, ensuring adaptability across heterogeneous fog environments. All parameters were validated through repeated trials under varying task loads and network conditions to confirm generalizability.

4 Results

4.1 Results of the fog-end collaborative prediction mechanism for transmission volume compression

In order to verify the operational performance of the smart city information resource collaboration system under fog computing, the effectiveness and accuracy of the proposed algorithms are verified respectively. The experiments were conducted on a representative fog-edge computing platform with the following hardware specifications: Intel Core i5-8265U processor (4 cores, 8 threads, 1.6GHz), 8GB DDR4 RAM, 256GB SSD storage, and Ubuntu 20.04 LTS operating system. No dedicated GPU was used, and all computations were performed on the CPU. This setup closely reflects the capabilities of typical low-power IoT gateways and fog nodes used in real-world deployments under constrained resource conditions. The hyperparameters in the experiments were determined through preliminary testing. The order of the autoregressive model was selected based on the Akaike Information Criterion (AIC), the number of clusters k in K-means was chosen

using the elbow method, and the cost function weights in the KLED algorithm were fine-tuned through multiple trial experiments. All parameters were validated on separate test sets to ensure the robustness of the results. The study first used K-means clustering algorithm to divide the sensing terminals into 7 clusters, and generated bandwidth capacity based on Gaussian distribution $Wb_i = N(\mu, \sigma^2)$, where μ is the mean value of link i bandwidth capacity and σ represents the variance of link bandwidth variance. To reduce the chance error, the mean value of five independent replicate experiments was used as the experimental result for each experiment. The experimental results of the data fit validity of the prediction mechanism are shown in Figure 5.

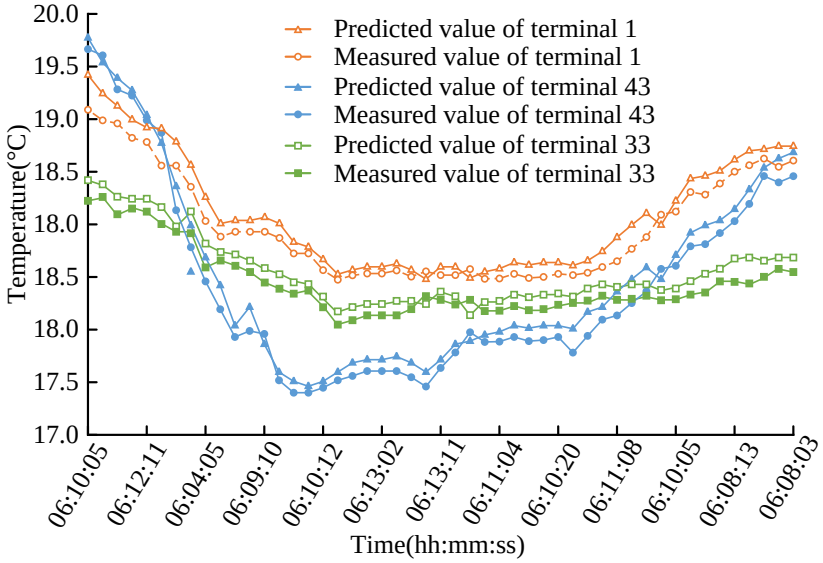
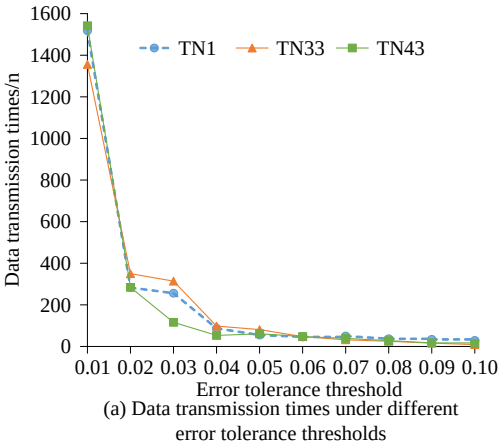
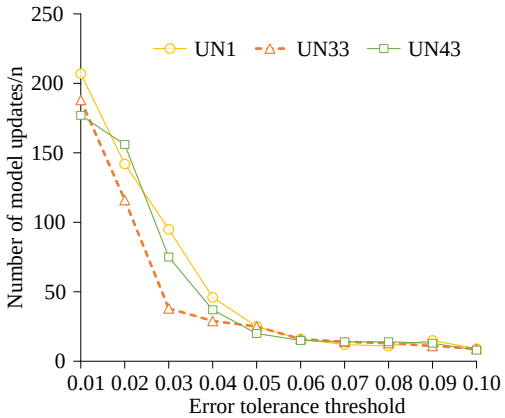


Figure 5: Fitting of measured value and predicted value in prediction mechanism

From the experimental results of fitting the temperature data in Figure 5, the predicted values obtained from the autoregressive model were highly fitted to the measured values in terms of variation trends and values. That is, the fog-end prediction mechanism could effectively compress the redundant data transmission volume under the edge network, which helped to reduce the pressure on the edge bandwidth. The validation results of the effectiveness of data transmission volume compression are shown in Figure 6.



(a) Data transmission times under different error tolerance thresholds



(b) Number of model updates under different error tolerance thresholds

Figure 6: Experimental results of the effectiveness of fog-end collaborative prediction mechanism to compress data transmission

As shown in Figure 6, a test range of 0.01 to 0.10 was selected based on preliminary experiments. When the threshold was set below 0.01, excessive synchronization requests were triggered, increasing communication overhead; when it exceeded 0.10, prediction accuracy dropped significantly. The selected range provided a well-balanced trade-off between transmission cost and prediction performance, making it suitable for edge computing environments. In the experiments on the effectiveness of data transmission volume compression, the reduction rate of data traffic within the edge network was used to focus on the reduction of data compression

rate. Experiments with different error tolerance thresholds on the number of data transmissions and the number of model updates were designed to verify the effect of the maximum error tolerance threshold on the number of communication interactions. From Figure 6(a), as the threshold value increased, the number of data transmissions decreased for all three terminals, especially in the interval from 0.01 to 0.04, while the trend was more stable in the interval from 0.04 to 0.10. Therefore, the higher the fitting accuracy of the prediction model, the less sensitive the fog-end collaborative prediction mechanism was to the error tolerance threshold. Figure 6(b) shows that as the threshold value decreased, the number of model updates gradually increased, i.e., the requirement for higher data accuracy, and thus the prediction model was required to provide more accurate data fit and prediction accuracy.

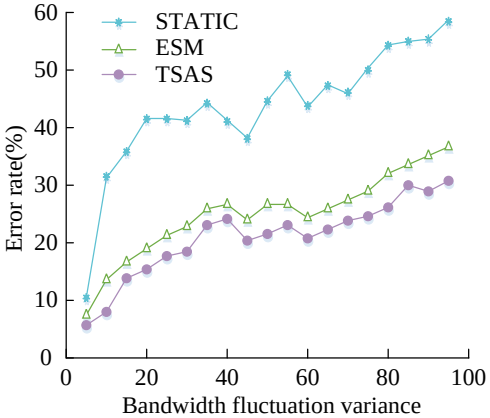
4.2 Performance of fog-end synchronization duration adaptive algorithm based on spatio-temporal correlation

Under the fog-end collaborative prediction mechanism, an effective and accurate synchronization wait time is required not only to reduce the chance of false positives, but also to shorten the waiting time of the device as much as possible without false positives, thus improving the efficiency of data acquisition. Therefore, the study used two metrics, namely, the misjudgment rate and mean absolute error (MAE), to verify the performance of the adaptive algorithm, and the experimental results are shown in Table 2.

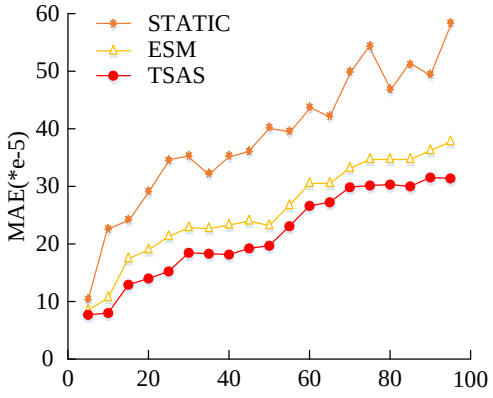
Table 2: Misjudgment rate and MAE of different algorithms

Algorithm	Misjudgment rate (%)			MAE (*e-5)		
	Maximum value	Average value	Minimum value	Maximum value	Average value	Minimum value
STATIC	52.0	30.9	13.7	5.52	3.62	1.53
ESM	39.9	18.5	15.8	5.06	3.04	1.39
TSAS	18.8	12.7	4.6	4.19	2.60	1.34

In Table 2, two static threshold schemes, STATIC algorithm and ESM, were selected experimentally as a comparison to verify the effectiveness of the TSAS algorithm. In terms of the average false alarm rate, the TSAS algorithm reduced the false alarm rate by 31.35% and 58.90% compared to the ESM and STATIC algorithms. Considering that the fog edge network had the characteristics of narrow bandwidth and weak connection, the study further analyzed the effect of bandwidth fluctuation of the fog edge network link on the false positive rate and MAE, and the experimental results are shown in Figure 7.



(a) Influence of bandwidth fluctuation misjudgment rate

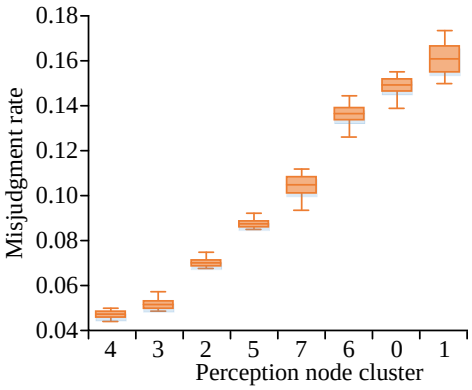


(b) Impact of bandwidth fluctuation on MAE

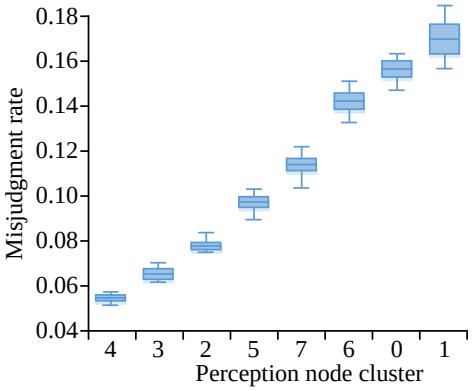
Figure 7: The impact of bandwidth fluctuation of fog edge network link on the error rate and MAE

As shown in Fig. 7(a) and Fig. 7(b), with the increase of the fluctuation variance of the link bandwidth, the false positive rate and MAE of the synchronous waiting time both increased. The comparison of the three algorithms showed that the false alarm rate and MAE of the TSAS algorithm were significantly lower than those of the STATIC algorithm and ESM. At the wave variance of 100, the false positive rate and MAE of TSAS algorithm were 30.5% and 31*e^{-5}, indicating that making full use of the spatial association information of the sensing terminal could effectively reduce the false alarm rate in the cooperative prediction mechanism. The results of further analysis of the influence of the distance between the terminal and the fog edge device on the false positive rate

based on the STAS algorithm and the ESM algorithm are shown in Figure 8.



(a) Error rate statistics of different sensing clusters based on STAS algorithm



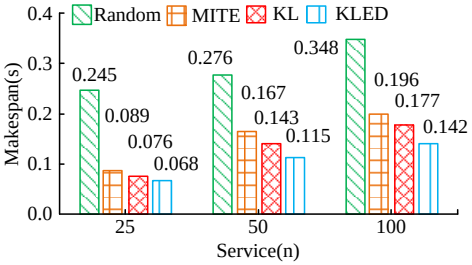
(b) Error rate statistics of different sensing clusters based on ESM algorithm

Figure 8: Experimental results of the influence of the distance between the terminal and the fog edge equipment on the error rate

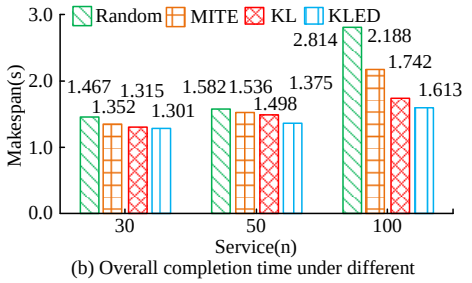
The fluctuation variance of each link was set to 10 in the experiment, and the horizontal coordinates were the different clusters ranked by the distance between the cluster center and the data aggregation node from smallest to largest. From Figure 8, both the mean and variance of the false positive rate increased with the increase of data transmission distance. When the transmission link was longer, the highest false positive rate of STAS algorithm and ESM algorithm was 16% and 17%, respectively. That is, the longer the transmission link is and the more complex the bandwidth variance is, the greater the impact on the false positive rate of the fog-end synchronization prediction mechanism.

4.3 Performance of collaborative information resource system for smart cities under fog computing

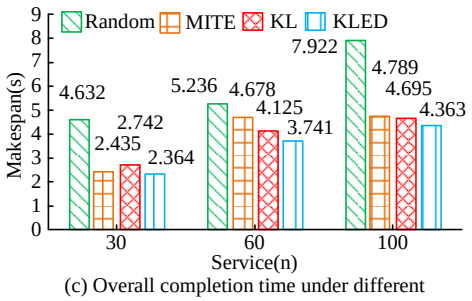
To verify the effectiveness of the KLED algorithm proposed in the study and the performance of the information resource collaboration system, the scientific workflow in Workflow Generator was selected as the service flow structure for the benchmark test. The workflow included four service structures, Montage, CyberShake, SIPHT, and LIGO Inspiral Analysis. Three comparative deployment strategies were used as baselines: Random Mapping, the Multi-Index Task-aware Edge scheduling algorithm (MITE), and the Key-Link algorithm (KL) implemented in this study. The KL algorithm followed a critical-chain-first placement strategy, assigning services along the shortest computing paths in the DAG while ignoring real-time communication or bandwidth dynamics. The experiments were repeated five times independently for each test, and the average value was taken as the final experimental result. The comparison of the overall service completion time of different algorithms under the four service structures is shown in Figure 9.



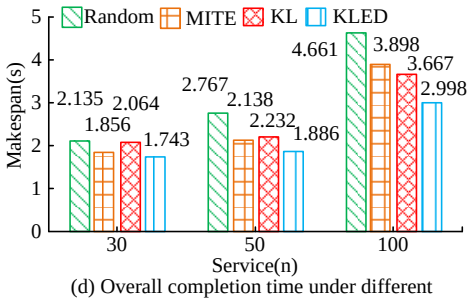
(a) Overall completion time under different scales of Montage service workflow



(b) Overall completion time under different scales of CyberShake service workflow



(c) Overall completion time under different scales of SIPHT service workflow



(d) Overall completion time under different scales of LIGO Inspiral Analysis service workflow

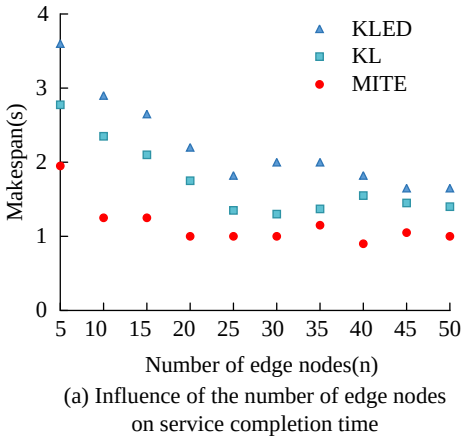
Figure 9: Comparison of overall service completion time of different algorithms under four service structures

Makespan refers to the total time required to complete all tasks within a workflow, measured from the start of the first task to the completion of the last one. It serves as a key metric to evaluate the overall scheduling efficiency and system responsiveness of service deployment strategies. In Figure 9, the makespan of the KLED algorithm proposed in the study substantially outperformed the Random deployment algorithm under four different service structures, and both outperformed the MITE algorithm and the KL algorithm. In the setting of service size of 100, the KLED algorithm reduced makespan by 19.77%, 7.41%, 7.07%, and 18.24%, respectively, compared to the KL algorithm for the four service structures of Montage, CyberShake, SIPHT, and LIGO Inspiral Analysis, i.e., the KLED algorithm outperformed the the other three algorithms. As the service size increased from 25 to 50 and 50 to 100, the makespan of KLED in the Montage structure increased by 40.87% and 19.01%, respectively. That is, the more complex the service process is, the operational performance requirements of the system increase as the communication relationships between subservices in the DAG increase. The study conducted impact proportional analysis experiments on the computation time, queuing waiting time and communication time that affect makespan, and the results are shown in Table 3.

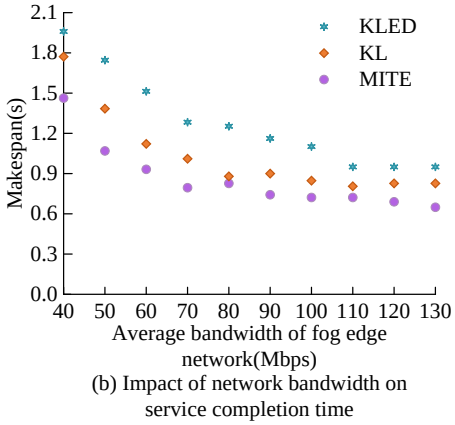
Table 3: Proportion of influence of calculation time, queue waiting time and communication time on makespan

Service size	Time type	Random	MITE	KL	KLED
	Waiting time	0.08	0.42	0.39	0.14
25	Communication time	0.73	0.38	0.35	0.43
	Calculated time	0.21	0.22	0.27	0.42
	Waiting time	0.12	0.47	0.41	0.22
50	Communication time	0.66	0.32	0.34	0.34
	Calculated time	0.24	0.23	0.25	0.43
	Waiting time	0.19	0.45	0.40	0.18
100	Communication time	0.63	0.38	0.40	0.40
	Calculated time	0.18	0.26	0.19	0.41
	Waiting time	0.75	0.78	0.77	0.73
1000	Communication time	0.20	0.14	0.15	0.11
	Calculated time	0.04	0.07	0.06	0.15

Table 3 presents the proportion of three-time components contributing to the overall makespan. Calculated time reflected the actual execution duration of tasks, communication time indicated the delay caused by data transmission between services, and waiting time represented the efficiency of resource scheduling. The results showed that when the service size was small, the Random algorithm exhibited the highest proportion of communication time, suggesting that its deployment strategy failed to minimize the transmission distance between services. MITE and KL showed a higher proportion of waiting time, indicating bottlenecks in task scheduling. In contrast, the KLED algorithm significantly increased the proportion of calculated time across different service sizes, demonstrating that system resources were more effectively utilized for execution after optimizing scheduling and transmission. As the service size grew to 1000, all four algorithms exhibited a sharp increase in waiting time proportion, primarily due to the limited parallelism, making queue delays the dominant factor in the overall makespan. The results of the KLED algorithm, MITE algorithm, and KL algorithm on the number of fog edge devices and network bandwidth on system performance for the Montage service with a service size of 100 are shown in Figure 10.



(a) Influence of the number of edge nodes on service completion time



(b) Impact of network bandwidth on service completion time

Figure 10: Effects of the number of fog edge devices and network bandwidth on system performance

In Fig. 10(a), the makespan of all three algorithms decreased gradually as the number of fog edge devices increased from 5 to 50, and the KLED algorithm outperformed the KL algorithm and the KL algorithm outperformed the MITE algorithm. The decrease of makespan was more obvious when the number of fog edge devices was increased from 5 to 15 than when the number of devices was increased from 15 to 50. Fig. 10(b) shows that as the available bandwidth increased from 10 Mbps to 150 Mbps, overall system performance improved accordingly. The most significant reduction in makespan was observed in the range of 40 to 100 Mbps. However, when the bandwidth exceeded 100 Mbps, the performance gains became marginal and the curve began to flatten, indicating that the communication bottleneck was largely eliminated. At this stage, computational and scheduling capacities became the primary limiting factors. Therefore, it is important to balance resource investment and performance improvement to avoid unnecessary resource overprovisioning.

To further validate the effectiveness of the proposed method, several representative approaches were selected as baseline methods, and their core mechanisms were reimplemented under the same experimental platform and dataset for quantitative comparison. The selected methods included: the sensing prediction mechanism based on throughput constraints proposed by J. Fei et al. [9], the data transmission optimization mechanism for vehicular networks proposed by W. Zhang et al. [11], and the multi-objective ant colony optimization–based service deployment strategy proposed by T. Huang et al. [15]. The evaluation metrics included false alarm rate, mean absolute error, and service completion time. The comparison results are presented in Table 4.

Table 4: Results of comparison with the existing methods

Method Source	False Alarm Rate (%)	MAE ($\times 10^{-5}$)	Service Completion Time (s)
Ref. [9] (Reproduced)	30.9	3.62	26.7
Ref. [11] (Reproduced)	27.4	3.20	26.5
Ref. [15] (Reproduced)	26.8	3.10	25.1
Proposed Method	12.7	2.60	21.8

In the table, the proposed method outperformed the three baseline methods in terms of false alarm rate, mean absolute error, and service completion time. Compared to Ref. [9] and Ref. [11], it demonstrated significantly better performance in prediction accuracy and synchronization. Compared to Ref. [15], it also achieved shorter completion time, indicating superior overall efficiency in both data transmission and task scheduling.

5 Discussion

To enhance the real-time processing of sensing data and improve service deployment efficiency in smart city scenarios, this study constructed a fog computing-based collaborative information resource system. It integrated sensing data, computational resources, and service dependency structures, and achieved intelligent scheduling and adaptive optimization at the edge layer through two core algorithms: TSAS and KLED. Specifically, the TSAS algorithm introduced a spatiotemporal correlation mechanism to dynamically adjust synchronization waiting times and prediction errors, thereby optimizing data compression and synchronization in high-frequency acquisition environments. The KLED algorithm combined K-means clustering with an improved scheduling strategy, taking into account resource heterogeneity and task dependencies among edge nodes, which effectively improved task parallelism and overall service execution efficiency.

Experimental results demonstrated that the TSAS algorithm reduced the false alarm rate to 18.8% and maintained the mean absolute error at 2.6×10^{-5}, thereby reducing unnecessary communication overhead while ensuring prediction accuracy. Meanwhile, the KLED algorithm achieved reductions in makespan of 18.24% and 7.41% compared to traditional KL and MITE deployment strategies across multiple workflow structures, and showed better scheduling stability and resource utilization under high-concurrency conditions.

Building on the above experimental results, the proposed TSAS and KLED algorithms also demonstrated clear advantages in terms of computational efficiency and deployment feasibility. The TSAS synchronization mechanism was based on an autoregressive model combined with exponential smoothing, involving only low-order matrix operations and sliding window updates. This resulted in significantly lower computational complexity compared to traditional deep learning-based prediction methods, making it more suitable for resource-constrained edge nodes. The KLED deployment strategy required maintaining only local service dependencies and scheduling states, with low memory overhead and structural stability, enabling efficient execution in heterogeneous devices and bandwidth-limited environments. The overall system adopted a modular design that facilitated integration into existing smart city edge infrastructures and supports good scalability. Therefore, TSAS and KLED not only outperformed traditional methods in terms of prediction accuracy and service latency, but also offered comprehensive advantages in computational efficiency and practical deployment adaptability.

While the experiments in this study focused on moderate-scale scenarios, the proposed system was

designed to support scalability in real-world deployments. TSAS executed independently on each edge device, requiring no global coordination, which enabled linear scalability as the number of devices increased. KLED, although involving clustering across multiple nodes, could be extended using hierarchical or region-based clustering frameworks to accommodate large-scale smart city environments with thousands of sensing points. Moreover, the modular architecture of both algorithms allowed parallel deployment and distributed processing, reducing the risk of performance bottlenecks. These design features made the system adaptable to future urban-scale deployments. Although security was not the primary focus of this study, data transmission was assumed to be protected by standard encryption, and basic access control could be applied to prevent unauthorized synchronization. The modular design of TSAS and KLED also allowed future integration of security mechanisms such as authentication and anomaly detection.

6 Conclusion

The convergence and development of scientific technologies such as artificial intelligence, the Internet of Things, and big data provide the basis for developing many intelligent analytical services, such as smart cities and intelligent transportation. The study combined fog computing, proposed a fog-end collaborative prediction mechanism to compress the amount of data transmission with high information redundancy in the edge network, and designed a KLED algorithm to reduce the overall computing time of the service and the corresponding delay of the service. The experimental results showed that the autoregressive model's prediction mechanism could effectively fit the changes of the temporal sensing data, and the TSAS algorithm could reduce the misclassification rate by about 31.35% and 58.90% compared with the STATIC algorithm and the ESM algorithm. The experimental performance results of the KLED algorithm showed that the highest waiting time sharing rate reached 73% when the service scale was 1000, and reduced the total calculation time of the service by approximately 13.12%, which effectively improved the service performance of the information. The service performance of the resource collaboration system was effectively improved. It is worth noting that the current experiments were conducted using a real-world dataset collected from 54 sensing devices in a specific urban scenario to verify the feasibility and effectiveness of the proposed approach. Although multiple datasets were not tested in this study, the core design of the TSAS and KLED algorithms was modular and adaptable to other fog computing environments. Future work will focus on validating the method across diverse datasets and deployment settings.

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Greylag Goose Optimization (GGO) Algorithm for Classifying Lung Cancer Disease

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It is to this effect that this paper proposes a Greylag Goose Optimization-based algorithm for the improvement of accuracy in case classification for lung cancer. The input data used for this study is prepared by scaling, normalization, and removal of null values. To get an optimal subset of features to improve the classification accuracy, the binary version of the GGO algorithm is compared with six other optimization algorithms: bSC, bMVO, bPSO, bWOA, bGWO, and bFOA, proving the efficacy of bGGO in feature selection. Multi-classification using many classifiers predicts MLP as the superior one with an accuracy of 91.8%. Hyperparameter tuning using GGO enhances the accuracy of MLP to 98.4%. Statistical evaluation with ANOVA and Wilcoxon's signed-rank test establishes the outcome to be highly significant ($p < 0.005$). The hybrid method of GGO + MLP reveals better robustness and efficien.

Povzetek: Hibridna metoda GGO+MLP je razvita za klasifikacijo pljučnega raka, ki z optimizacijo izbire značilk in hiperparametrov doseže kvalitetno klasifikacijo.

1 Introduction

Lung cancer is a very critical and life-taking disease globally. According to the most recent estimates by the World Health Organization, more than 7.6 million deaths annually occur worldwide because of lung cancer. Moreover, the total incidence cases of cancer are projected to increase to nearly 17 million cases in 2030[1]. Screening of cancer at an initial stage is very crucial because it normally metastasizes and becomes incurable once it has significantly spread. Diagnosis of lung cancer is challenging because the symptoms only appear at an advanced stage where successful treatment outcomes become very hard to achieve. Imaging techniques used in taking images of the lungs for assessment include magnetic resonance imaging, Positron Emission Tomography, Computed Tomography, and X-ray. Lung cancer detection makes use of image processing and deep learning techniques where precision can be enhanced by implementing these methodologies. Detection and identification of the shape, dimension, and position of a tumor is a difficult task. The timing of its detection is very important so that medical interventions can be done on time. However, radiologists still face difficulty in distinguishing between malignant and benign nodules. Identifying malignant nodules from benign ones through naked-eye appearance is subjective and the results differ among multiple observers and cases. Overall, the accuracy of classification for nodules among expert radiologists was more significant compared to that by non-expert radiologists. The idea of getting accurate, reliable, and unbiased analysis motivated the development of computer-aided diagnosis systems [3].

Successful application of ML techniques and neural networks in lung cancer classification was performed as in [4,5]. Very promising models could be obtained in applying machine learning to both classification and regression by using optimizers and ensemble regression models. Techniques developed for biomedical image recognition can become the very first diagnostic tools that show diseases as in [6]. However, constructing very efficient classifiers with appropriate features for pulmonary nodules is of essence in the construction of dependable CBIR and CAD systems. Conventionally, a CAD system embodies two phases: feature extraction and categorization. CBIR normally makes use of a host of visual elements such as texture, shape, and granulometry to create the search index as reported in. To build effective

machine learning architecture, there is a need for skillful combinations of hyper-parameters that can improve accuracy and performance in classification. The manual techniques for solving combinatorial problems are time-consuming, inefficient, and at times overwhelming. Proposals have been made to use metaheuristic algorithms in optimizing the process of determining which hyperparameter combination will result in the highest performance.

These optimization techniques generally get inspiration from some natural phenomenon for global, local, and sometimes random searches for the best solution. Metaheuristic algorithms are recognized to be those techniques that find viable solutions of optimization with very minimal processing power. Swarm intelligence algorithms, which form a subset of Metaheuristics, have already been applied successfully to several complex real-world problems in scientific, engineering, and medical domains especially for lung cancer diagnosis as in [7].

Metaheuristic algorithms are iterative methods that tend to evaluate many possibilities in the quest for the optimal solution. They are applied in the identification of the ideal combination of weights for use in addressing the problems of feature extraction and classification. Greylag Goose Optimization has already been applied to different optimization problems, returning very promising results for health applications like lung cancer diagnosis [8]. In this work, it uses GGO as the metaheuristic optimization strategy. The reason for this choice is that, overall, it provides a good record across similar optimization scenarios. Besides, it includes some features that might benefit it over others in certain aspects. A mix of ML methods with a metaheuristic algorithm seeks high accuracy and performance.

Obviously, performance tuning in disease detection, like lung cancer, may provide benefits by giving better diagnostic accuracy and early initiation of treatment. In this paper, it is proposed to combine MLP with GGO metaheuristic algorithm for better optimization of parameters to enhance its learning and classification capability of complex patterns in the data. This paper is therefore aimed at integrating some preprocessing strategies with the GGO-MLP algorithm to improve the classification accuracy of lung cancer textual data. First, pre-processing of the input data is done in which data gets scaled, normalized, and NULL values get removed. After pre-processing, the next task to be done is to extract the optimum set of features that might enhance the accuracy of lung cancer classification. In GGO method, extraction is made in binary format in search of cancerous lung states. The next process is the classification of lung disease based on extraction of unique features. The classification step involves many classifiers, such as SVC, DTC, RFC, KNC, and MLP. The results proved that MLP is the best classifier. The hyperparameter of the MLP model is tuned by GGO, where its performance was evaluated against six other optimizers: SC, MVO, PSO, WOA, GWO, and FOA. GGO with the MLP model gives the best results for lung cancer classification.

The following important research questions are intended to be addressed by this study:

Does bGGO perform better than current optimization methods when it comes to feature selection for the classification of lung cancer?

In comparison to alternative feature selection techniques, how does bGGO increase classification accuracy?

How does the performance of MLP change when hyperparameter tweaking is done via GGO?

These inquiries direct our examination of the suggested method's efficacy.

This paper is organized as follows: An overview of the state-of-the-art literature is given in Section 2. Section 3 presents a detailed explanation of the suggested methodology.

The discussion of the experimental results is presented in Section 4. The findings and suggestions for the future are presented in Section 8.

2 Related work

Machine learning (ML) and deep learning (DL) have been widely researched for lung cancer classification. Early detection is critical as it can affect the survival rate of the patient. It offers a balanced review of the domain, covering baseline as well as state-of-the-art techniques for lung cancer classification, ranging from image-based models to tabular data driven approaches.

For lung cancer classification, machine learning approaches such as Support Vector Machines (SVM), Neural Networks, and Decision Trees have been in practice for a long time. The latest studies proposed deep learning methods with their variants, especially Convolutional Neural Networks (CNNs), because of their proficiency in extracting spatial features from imaging data. However, CNNs are often redundant with the basis of features and require the generation of a large, labelled dataset.

There is a solution proposed by Tehnan IA Mohamed et al. [9] to this problem. The proposed hybrid CNN and metaheuristic approach using EOSA to find the best weights and biases for the CNN model. Despite successfully enhancing the classification accuracy, the limitations of computationally excessive training on the vast datasets remain.

Zeyu Ren et al. [10] have brought forward the idea of LCGANT being a deep convolutional Generative Adversarial Network (GAN) architecture. It is notable that LCGANT can produce artificial images of lung cancer and the network VGG-DF with transfer learning can classify these images with 98.5% accuracy. Nonetheless, LCGANT is heavily dependent on synthetic data, which is its drawback in terms of generalization to the real world.

For lung cancer classification by using features selection and models optimization, metaheuristic optimization techniques have been used. An optimized Random forest classifier full-back aided by a K-means visualization method to improve the feature selection was proposed [11]. P. Mohamed Shakeel et al. [12] assessed biochemical lung malignancy attributes with an ensemble learning technique guided by a wolf prey algorithm, obtaining a favourable figure of prediction (99.48 percent).

Researchers have conducted several studies on hybrid optimization techniques, like the combination of Whale Optimization Algorithm (WOA) with Support Vector Machines (SVMs). Surbhi Vijh et al. [13], introduced an improved method using WOA and SVM techniques for feature selection to achieve accurate findings for lung cancer detection. WOA-SVM showed outstanding performance in CT scan classification with an accuracy of 95% and sensitivity of 100%. Despite being fast, the algorithms driven by WOA experience issues such as premature convergence.

The proposed Greylag Goose Optimization (GGO) approach outperforms the limitations of existing metaheuristic algorithms by adjusting exploration and exploitation phases dynamically to avoid local optima. Compared to CNN-based approaches relying on spatial feature extraction, GGO-MLP is designed for structured tabular data, reducing computational complexity and improving interpretability. By jointly optimizing feature selection and hyperparameters, GGO-MLP achieves a good balance between accuracy and computational overhead. However, our findings indicate that CNN-based methods are generally plagued by feature redundancy, while traditional metaheuristics are incapable of adapting to dynamic feature spaces. Our strategy optimally balances feature selection and classification performance through GGO-guided hyperparameter tuning. The comparison in Table 1 can demonstrate that PSO-SVM achieves especially superior performance among all these techniques to accurately identify the instances of lung cancer with a 99% specificity and 97.6% accuracy. CNN-based approaches lag with tabular data due to their focus on spatial features. In contrast, metaheuristic algorithms tend to find a solution too rapidly and get stuck, since they fail to change their group dynamics as Group Gradient Optimization (GGO) is able to. This can make them less effective at discovering optimal solutions.

3 Material and methods

3.1 Greylag goose algorithm for optimization (GGO)

Table 1: Comparison summary between EOSA-CNN, WOA_SVM, and PSO-SVM algorithms

Method		Accuracy	Sensitivity	Dataset (Size)	Year
[9]	**EOSA-CNN**	95.2%	93.8%	IQ-OTH/NCCD (500)	2023
[12]	**WOA_SVM**	95.0%	100%	Private (220)	2020
[14]	**PSO-SVM**	97.6%	99.0%	Kaggle (500)	2022
	Proposed	**98.4%**	**97.7%**	Kaggle (284)	2024

The GGO technique generates a set of individuals at random to begin the process, each of which will stand as a possible solution for the problem. These are defined as individuals Yp (p = 1, 2, …, n), where n is the number of the total population of individuals, which forms the GGO population. An objective function, represented by Fn, is chosen for the evaluation of the members of the group. The best solution, represented by Z, is attained from the analysis of an objective function for every individual or agent represented by Yp.

The algorithm, GGO, exhibits dynamic group behavior by splitting the population into two groups—an exploration group of size n1 and an exploitation group of size n2. Automatically, the number of solutions in each group is updated with respect to the optimal solution in every iteration. The exploitation group comprises of n2 agents, while the exploration group includes the remaining n1 agents, as shown in Figure 3. At the start, GGO assigns 50% of its population for exploration and 50% for exploitation. In this scenario, the number of agents in the exploration group will decrease by n1 and increase by n2 in the case of the exploitation group. If there is no change in the objective function value of the best solution for three continuous iterations, then the algorithm will increase the number of agents in the exploration group, n1, to find a different best solution and probably avoid local optima [15].

• Explore Operation: The two important tasks of exploration are locating the more interesting regions in the search space and avoiding falling prematurely onto a local optimum, especially when an optimal solution is being progressed toward.

–Best solution: In this strategy, the geese explorer will seek good new areas to explore around its current position. It does this by iteratively assessing a lot of possible neighbors and then chooses the best solution on how fit that solution is. The following equations are used by the GGO method to do this, modifying the B and D vectors: B = 2b.m1 −b and D = 2, throughout iterations while using a parameter that is progressively adjusted from 2 to 0:

$$Y(k+1) = Y*(k) - B.|D.Y*(k) - Y(k)| \quad (1)$$

where Y(k) presents an individual at iteration k. The Y∗(k) denotes the optimal location of the leader (best solution). The Y (k + 1) represents the adjusted location of the individual. The values of m1 and m2 values are randomly changing within the range of 0 to 1.

The equation below will be employed by selecting three random search individuals (paddlings), referred to as YPaddle1, YPaddle2, and YPaddle3, to ensure that the individuals are not influenced by a single leader position, hence promoting greater exploration. If |B| is higher than or equal to 1, the current search agent's position will alter as follows.

$$Y(k+1) = w1*YPaddle1 + p* w2* (YPaddle2 - YPaddle3) + (1 - p) * w3 * (Y - YPaddle1) \quad (2)$$

where (w1, w2, and w3) values are adjusted and updated within the range of 0 to 2. The parameter p exhibits an

exponential decrease and is determined by the equation shown below.

$$p = 1 - (\frac{k}{k_{max}})^2 \quad (3)$$

where the iteration number is denoted as “k” and “kmax” specifies the most possible iterations.
The second procedure of updating is as follows for m3 values greater than or equal to 0.5, where the values of b and B vector values are reduced.

$$Y\ (k + 1) = w4 * |Y*(k) - Y(k)|.\ eal.cos\ (2\pi l) + [2w1(m4 + m5)] * Y*(k) \quad (4)$$

where a is a fixed value, l is a randomly selected value from a range of −1 to 1. The w4 parameter is adjusted within the range of 0 to 2, whereas m4 and m5 parameters are modified within the range of 0 to 1.
Operation of Exploitation: The task of the exploitation group is to improve existing solutions. At the end of each round, the GGO selects the best fitness individual and gives him due recognition. In achieving its exploitation objective, GGO applies two different strategies, which are described as follows.
– Going concerning the best explanation: The following formula is used to step forward toward the best solution. Three sentries, YS entry1, YS entry2, and YS entry3, instruct other agents YNonS entry to update the locations toward the predicted location of the prey. The following formula shows the process of updating locations.

$$Y1 = YS\ entry1 - B1.\ |D1.YS\ entry1 - Y|,$$
$$Y2 = YS\ entry2 - B2.\ |D1.YS\ entry2 - Y|, \quad (5)$$
$$Y3 = YS\ entry3 - B3.\ |D1.YS\ entry3 - Y|$$

where the (B1, B2, B3) values are determined by the equation B = 2b.m1–b, where b is a constant. Similarly, the values of D1, D2, and D3 are determined by the equation D = 2m2. The modified population locations, Y (k + 1), can be determined by averaging the three solutions: Y1, Y2, and Y3 as follows.

$$Y\ (k + 1) = \overline{Yl}|_0^3 \quad (6)$$

The second mathematical lemma that can be utilized in the study of the GGO algorithm during the exploitation process is the Triangle Inequality. Essentially, one of the basic definitions for metric spaces is the Triangle Inequality: for any triangle, the length of one side is less than or equal to the sum of the other two sides. For GGO, it means that any two agents are closer than or equal to the sum of distances of these two agents from the third in the search space. So, a fine solution lies around the optimum response-leader-in flight. Consequently, some agents are incentivized to improve the solution by searching the space around the optimum solution, which is called YFlock1. To overcome the limitation of local optima, GGO makes use of the process affecting local and global optima based on the following equation.

$$Y\ (k + 1) = Y(k) + C\ (1 + p) * w * (Y - YFlock1) \quad (7)$$

The third mathematical construct that can be utilized in the investigation of the GGO algorithm in its effectiveness at removing the issue of local optima is the Law of Large Numbers. It states that the sample average will approach the population average as the sample size becomes large, and therefore is an elementary concept in probability theory. In the context of GGO, what this means is that, eventually, as the size of the swarm goes to infinity, the swarm will converge towards the global optimum.
GGO's one key benefit is that it can tradeoff exploring and exploiting dynamically. It is actually accomplished through an adaptive weight mechanism that gets set at a number of iterations. It is a validated balance among iterations using statistical monitoring of performance improvement rates. Figure 1, which shows the agent reclassification process between exploration and exploitation groups, illustrates the GGO decision-making criteria.

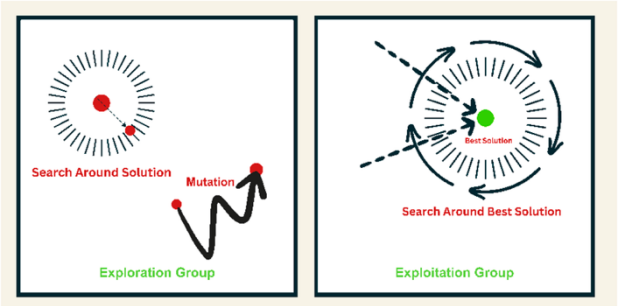


Figure 1: The GGO exploration and exploitation.

The Greylag Goose Optimization algorithm has outstanding exploration capabilities with the introduction of a mutation approach and scanning participants of the group in performing exploration. With such a strong explore ability, GGO will suffer from delays in convergence. Algorithm one is the pseudo-code of GGO. In algorithm one, the GGO is provided with certain basic parameters, such as population size, mutation rate, and number of iterations. It therefore divides the participants into two based on GGO: one group carrying out exploratory labor and another group doing the exploitative labor. In its iterative search for the optimal solution, it will dynamically change the size of each group. To introducing diversity and to ensure that the space has been fully explored, GGO applies a random reordering of the responses at each iteration.
The algorithm randomly selects initializations from a population and assesses the performance with placeholder functions. It walks through random mutations and uses crossover with the best agent. Exploration probability of Dynamic Balancing decreases over time, which will foster exploitation in later phases. GGO dynamically adjusts agent roles to avoid premature convergence and enhance search effectiveness.

A solution parameter from the exploration group can be shifted into the exploitation group in a single iteration. The GGO's self-designed mechanism guarantees the position of the leader during the entire process. The GGO algorithm works toward the procedure for upgrading the roles in the exploitation group (n2) and the exploration group (n1). The parameter m1 is modified iteratively according to the equation m1 = $d(1 - \frac{k}{k_{max}})$, where k depicts the current iteration, d denotes a constant, and k_{max} shows how many iterations there are. GGO, after every iteration, modifies the individuals in the search space and randomizes their order to shift the roles between the groups: exploration versus exploitation. It finally retrieves the optimal solution for a solution space.

Algorithm 1: Proposed GGO algorithm.

1: Initializing GGO population Yj (j = 1, 2, ..., n), population size is n, the total iterations number is kmax, and an objective function Fn.
2: Initializing all GGO parameters b, B, D, a, l, d, w, m1 - m5, w1- w4, B1-B3, D1, - D3
3: Set k = 1
4: Determine each agent's objective function (Fn) Yj.
5: Set Z = greatest agent position
6: Revise the solutions in the groups for exploration (n1) and exploitation (n2).
7: while k ≤ kmax do
8: for (j = 1: j < n1 + 1)
9: if (k%2 == 0) then
10: if (m3< 0.5) then
11: if (|B| < 1) then
12: Update the current search agent position as in Equ (1).
13: else
14: Select three random search agents YPaddle1, YPaddle2, and YPaddle3
15: Update (p) by the exponential form as in Equ (3).
16: Update the current search agent position as in Equ (2).
17: end if (Line11)
18: else
19: Update the current search agent position as in Equ (4).
20: end if (Line10)
21: else
22: Update individual positions as in Equ (7).
23: end if (Line 9)
24: end for (Line 8)
25: for (j = 1: j < n2 + 1)
26: if (k%2 == 0) then
27: compute Y1, Y2, Y3as in Equ (5).
28: Update individual positions as in Equ (6).
29: else
30: Update the current search agent position as in Equ (7).
31: end if (Line 26)
32: end for (Line 24)
33: Calculate Fn for each Yp
34: Update parameters
35: Set k =k + 1
36: Adjust beyond the search space solutions
37: if (Best Fn is the same as the previous two iterations) then
38: Increase the solutions of group (n1)
39: Decrease the solutions of group (n2)
40: end if (Line 37)
41: end while (Line 7)
42: Return best agent Z

Efficiency and convergence speed are balanced by the GGO stopping criterion. There are three circumstances that cause the algorithm to stop. The first is the maximum Iterations that permit exploration and exploitation, it operates for a predetermined number of iterations. The second is the fitness improvement threshold that saves resources, it stops if the optimal fitness does not increase by a certain amount. The diversity-based stagnation detection is deemed stagnant and halts if all agents have comparable feature subsets. By eliminating pointless computations and early convergence, these criteria assist GGO in maintaining a balance between computational efficiency and solution quality.

3.2 The proposed binary GGO optimization algorithm

GGO Optimization Algorithm: This is a better approach to the optimization of the feature selection of MLP parameters. This technique uses a binary format in the selection of features and optimizes the set of used features to improve MLP's performance.

Feature selection problems are limited to binary 0, 1 constituents of a search space, indicating how relevant a certain feature is. Thus, in the binary GGO method, the continuous GGO values that will be proposed in this section are transformed into a binary format, [0, 1], directly relating to the feature selection process. The basic objective of the procedure, as formulated in equations 11 and 12, is to convert the continuous data into binary data using the following Sigmoid function.

$$Bi_t^* = \begin{cases} 1 & if\ sigmoid\ (Bi_t^*) \geq 0.5 \\ 0 & otherwise \end{cases} \quad (8)$$

$$Sigmoid(Bi_t^*) = \frac{1}{1+e^{-10(Bi_*^i - 0.5)}} \quad (9)$$

where Bi_t^* reflects the best solution at a given iteration (t). Algorithm 2 presents the proposed bGGO stages used for selecting the optimum feature set, enhancing the Caries' case classification accuracy.

Algorithm 2: bGGO algorithm.

1: Initialize population of GGO, objective function, and GGO parameters
2: Convert the solution to binary [0 or 1]
3: Calculate the objective function for each agent and get the best agent position
4: Update Solutions in the exploration group
5: Update Solutions in the exploitation group
6: while k ≤ kmax do
7: for (j = 1: j < n1 + 1)
8: if (k%2 == 0) then
9: if (m3< 0.5) then
10: if (|B| < 1) then

11: Update the current search agent position in the exploration group
12: else
13: Update the current search agent position based on the three random search agents
14: end if (line 10)
15: else
16: Update the current search agent position
17: end if (line 9)
18: else
19: Update individual positions
20: end if (line 8)
21: end for (line 7)
22: for (j = 1: j < n2 + 1)
23: if (k%2 == 0) then
24: Update the current search agent position in the exploitation group
25: else
26: Update of the current search agent position
27: end if (line 23)
28: end for (line 22)
29: Convert to binary the updated solution
30: Calculate the objective function
31: Update parameters
32: Adjust beyond the search space solutions
33: Update the exploration group Solutions
34: Update the exploitation group Solutions
35: end while (line 6)
36: Return best agent

3.2 Multilayer Perceptron (MLP) Model

Application of the multilayer perceptron model, inspired by the neural architecture of the human brain, has particularly superior performance in nonlinear simulations of complex systems. They can resolve nonlinear structure prediction problems [17]. They learn how to solve a problem and discover relationships that underlie the data. For this purpose, a large amount of data is fed during the training process which is based on the learned relationships to calculate the desired output. The most frequently applied neural network model is the back-propagation network. The neural network has neurons that act in parallel for each layer. Every layer is fully connected with the previous and next layers.

Algorithm 3: Pseudo code of MLP Model.

1-Initialize Multilayer Perceptron MLP with input and output dimensions (number of features), number of hidden layers, dimension of hidden layers, activation function, batch size, Num epochs, and learning rate.

2- Set MX the input matrix, every row in MX is an input vector.

3- Set The output matrix MY, every row in MY is the corresponding output vector.

4- Initialize weights matrices W[l] for l = 1 to L, where each weight W[l][j][k] is a connection between layer l's neuron j and layer l+1's neuron k.

5- Initialize Biases B[l] for l = 1 to L-1, where each bias B[l][j] is the bias for layer l+1's neuron j.

6- Repeat until the error is within the acceptable range or maximum iterations are reached:

7- Forward pass:

8-For l = 1 to L:

9- Calculate the weighted sum for every neuron layer l+1 neurons.

10-Apply activation function A[l] to every layer l+1 neurons:

11-For each sample in the batch:

12-Compute the loss between predicted output and actual label (cancerous or non-cancerous).

13 - Backward pass:

14- For l = L to 1:

15-Compute the gradient of loss concerning the weight matrix Wi and the bias vector bi.16-Update the weights and biases by subtracting the product of the learning rate and the

corresponding gradients from the current values for output and hidden layers.

17- End of the training process.

4 The proposed framework

This phase of data processing involves primarily removing null values and normalizing and scaling data. The serious part of the phase is preparation and expansion of the data. This study used feature selection methods to perform 7 optimization methods in binary form which are-GGO [15], Sine Cosine Algorithm (SC) [17], Mean-variance optimization (MVO) [18], Particle Swarm Optimizer (PSO) [19], Whale Optimization Algorithm (WOA) [20], Gray Wolf Optimizer (GWO) [21], Falcon Optimization Algorithm (FOA) [22]. In the second step, the feature selection process is applied, with the proposed feature selection method. Using bGGO, the found features are extracted. The aim of this step is to get the best features that will make the input data be classified with greater accuracy. This step has the benefit of reducing the total number of features by removing irrelevant features. The input data has been classified using ML classifiers and features selected have been chosen based on bGGO. The list of the suggested ML models used in this research includes the SVC, DT, RFC, 1 KNN, and MLP models. The MLP model used must have its parameters optimized to best exploit the proposed optimization technique. Therefore, the selection of the most optimal set of classification parameters is the object in view at this stage of preprocessing.

It generates the first population of solutions for all possible configurations of the parameters. A value of associated fitness is assigned to each Greylag Goose, with respect to the quality of its key regarding the validation set. Individuals search the solution in a systematic way in the population to discover the best solutions of the search space. The GGO optimizes in the same way an iterative action performed by it which refines the decisions step by step towards Pareto dominance to get the optimal configuration of the parameters in MLP. The weighted vectors are used by GGO to drive the people to the correct position, which is calculated by the population's fitness score after every generation. These algorithms keep on changing the positions of individuals in the way of coming very near the optimal action because of the iterative work of GGO. The GGO performs an iterative action that

refines the solutions step by step towards the Pareto front to obtain the optimal configuration of MLP parameters. This algorithm stops when either a convergence threshold has been met or after many iterations. Thereafter, the configuration for which the value of fitness is maximum is considered as the best, optimal solution.

This study has developed a model for how GGO can help in enhancing the tuning parameters of MLP. The optimization of the parameters of MLP is associated with achieving the highest level of classification accuracy and performance. The parameters that require optimization should be identified prior to using the GGO to alter the values in MLP. Figure 1 declares a sequential process of the proposed framework.

For GGO and MLP, choosing the right hyperparameters is essential to performance optimization. For GGO population size, it maintains computational efficiency and guarantees exploratory variety, a balanced size was chosen. The exploration and exploitation of these parameters avoids early convergence and increases search efficiency, GGO constantly modifies agent responsibilities. The MLP Structure tests for appropriate feature representation without overfitting were used to identify hidden layers. The ReLU activation function was selected due to its ability to handle non-linearity well. The learning rate is optimized by GGO for faster, oscillation-free convergence. Adam was chosen due to its adaptability, and the batch size was modified to account for generalization and training speed. Multiple hidden layers with optimal hyperparameters and tweaking via GGO are features of the MLP architecture, which increases classification accuracy.

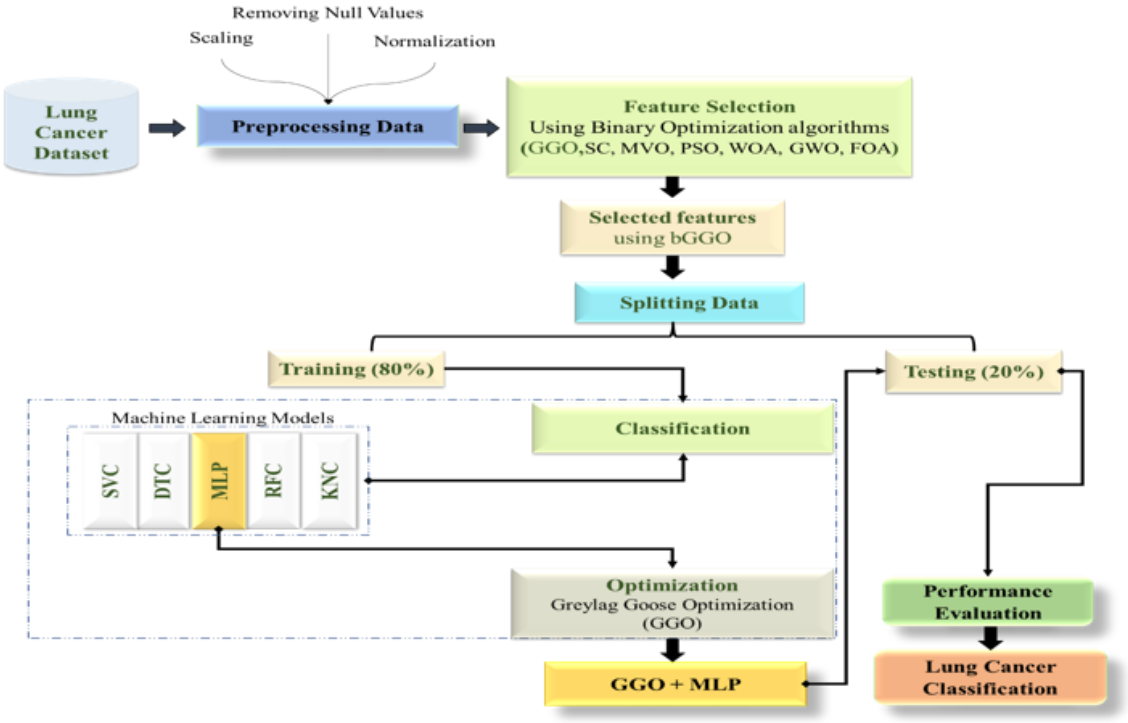


Figure 2: The proposed lung cancer classification framework

5 Experimental results

5.1 Experimental setting

The tests carried out tests assessed the proposed algorithm for various experimental conditions. In these tests, some traditional mathematical functions were used as benchmarks to determine the minimum values for a given range of variables. Such mathematical functions are usually used in literature to compare the performance between an optimization technique against others, and there are many variations of these optimization techniques. The suggested Greylag Goose Optimization algorithm has been compared with six famous optimization techniques to show better performance and efficiency. In the present study, comparisons are drawn among GGO, SC, MVO, PSO, WAO, GWO, and FA. All these algorithms have been chosen due to their popularity and their practical importance, which has made them quite well-known.

Technical specifications of the study platform included: primary memory of 16 GB, Intel Core i7 CPU, and GeForce RTX2070 Super 8 GB RAM GPU. The details of the specification of the software included: Ubuntu 20.04 as the operating system, with TensorFlow 1.15, CUDA9.0, and Cudnn7.1, and Python 3.7 for Spider IDE.

5.2 Dataset description

Machine learning and data science experts can utilize this dataset to make prediction models of the diagnosis of lung cancer, to study the effect of different characteristics related to cancer, and to make algorithms for the treatment and prevention of cancer. This project works with a data set named "Lung Cancer Dataset," collected and uploaded to Kaggle. The pre-enabling classification of cancer and the pre-enabling systems have facilitated various sites through which individuals can check whether they have cancer problems at a throwaway price.

It also aids specialists in making decisions based on the risk profile for cancer. This information is scooped from the website, which is owned by the online lung cancer prediction system, located at: https://www.kaggle.com/datasets/mysarahmadbhat/lung-cancer.

The dataset consists of 284 samples and 15 characteristics. The characteristics contain categorical and numerical features, which were preprocessed with one-hot encoding and normalization as needed. The dataset was divided between training and testing sets using an 80-20% segmented split to ensure class distribution balance. A cross-validation procedure with k folds (k=5) was used to assure the model's resilience, preventing overfitting and allowing a more generic assessment of performance. The one-hot encoding is used for categorical features to transform non-numerical input for model training. To address class imbalance, we used stratified sampling in the training/testing split to ensure proportional class representation.

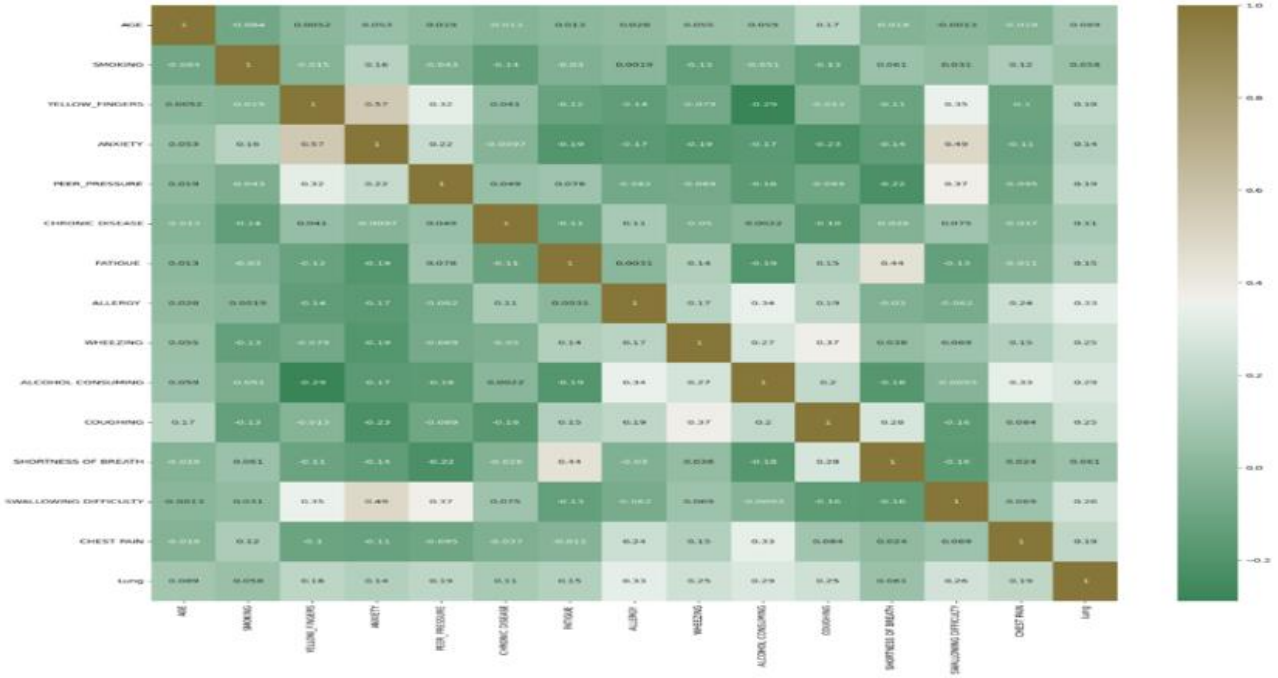


Figure 3: Scatter plot for each feature in the dataset.

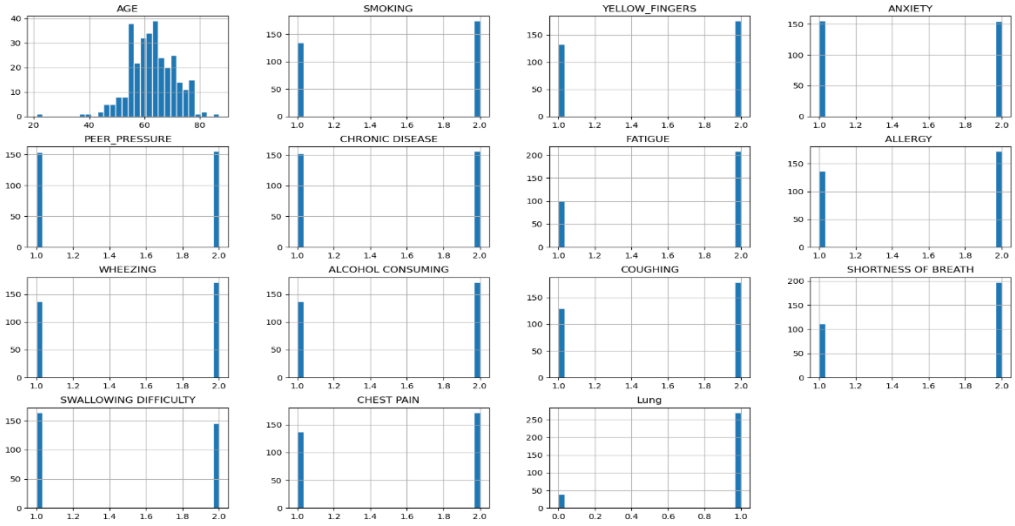


Figure 4: A correlation matrix between features in the dataset.

The input features include attributes of the dataset such as Gender, Smoking, Age, Yellow fingers, pressure, Anxiety, Chronic Disease, Swallowing Difficulty, Allergy, Fatigue, Wheezing, Shortness of Breath, Coughing, Alcohol, and Chest pain. The attributes count for sixteen, and the occurrences are 284. The above variables classify the output variable being Lung Cancer. Figure 3 shows the scatter plot below; it demonstrates the relation between the variables of the Lung Cancer input and output datasets. Figure 3 presents a correlation matrix heatmap for the characteristics of the dataset at hand.

Correlation Matrix is another important statistical tool applied in ascertaining the interrelationship between variables in a data set is the correlation matrix. The correlation matrix normally contains the pairwise correlation coefficients for each pair of variables moving from -1 to +1 and states the direction and strength of each interaction. From the correlation matrix, the picking of variables that are positively or negatively correlated will be based on which ones are best to investigate relationships, patterns, and potential predictors in the data.

This information becomes especially important to predictive modeling for handling multicollinearity issues, detecting dimensionality reduction, and selecting relevant characteristics. The correlation matrix of the used dataset is shown in Figure 4.

This study focuses on tabular data for lung cancer detection rather than imaging because deep learning for pictures requires significant resources, but machine learning techniques such as MLP effectively handle tabular data. Tabular data displays patient features and clinical history in structural manner, which improves decision-making clarity. Many tabular datasets are available and easily useable rather than imaging datasets that require extensive preparation to be usable.

Seven optimization algorithms, mentioned below, have applied the feature selection in binary form: Greylag Goose Optimization Gray Wolf Optimizer Mean-variance Optimization Whale Optimization Algorithm Sine Cosine Algorithm Particle Swarm Optimizer Falcon Optimization Algorithm the Below Table 2 represents the performance evaluation based on all these techniques of feature selection. From the table, it can be concluded that the results obtained in the proposed bGGO approach are better than those in other binary methods of feature selection.

Table 2: Evaluation of the suggested (bGGO)feature selection technique in comparison to other competitive techniques.

	bGGO	bSC	bMVO	bPSO	bWAO	bGWO	bFA
The Average error	0.774303	0.79150	0.80510	0.82530	0.82510	0.81160	0.8237
The Average Selected size	0.727103	0.92710	0.86950	0.92710	1.09050	0.84990	0.9616
The Average Fitness	0.837503	0.85370	0.86510	0.85210	0.85990	0.85980	0.9040
greatest Fitness	0.739303	0.77400	0.76840	0.83240	0.82400	0.83760	0.8227
lowest Fitness	0.837803	0.84090	0.88350	0.90010	0.90010	0.91380	0.9203
Standard deviation (SD)Fitness	0.659803	0.66450	0.66610	0.66390	0.66610	0.66510	0.7007

Figure 5 is showing the average error of the proposed technique against nine more of the feature selection strategies. From the figure, what can be seen is that the bGGO technique shows the lowest average error in graph form, underpinning its robustness.

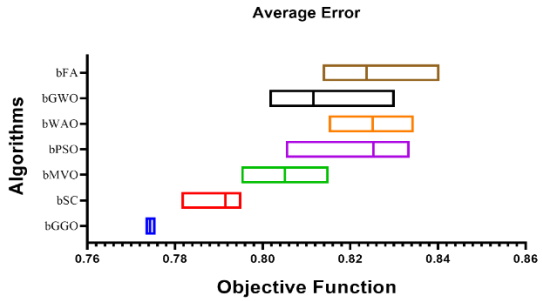


Figure 5: Results obtained with bGGO are of the lowest average error, underpinning the effectiveness and robustness of this feature selection technique.

To validate performance gains, we employed ANOVA and Wilcoxon signed-rank tests. For Hypothesis(H1) The ANOVA test yielded a p-value < 0.005, showing that GGO-MLP is statistically different from others. Wilcoxon Results compared GGO-MLP to baseline models. GGO-MLP demonstrated higher classification performance and structural improvements throughout numerous iterations, as validated by a p-value < 0.005.

Table 3 presents the performance of bGGO in combination with the existing feature selection strategies for different measures. It must be noticed that p-values were obtained using a comparison of results from each pair of algorithms, but the proposed feature selection technique shows statistically significant superiority.

It assumes that the mean values m of bGGO under H0 are equal to the mean values of bGWO, bPSO, bWAO, bSC, bMVO, and bFA. The alternative hypothesis, H1 considers the mean values of bGGO to be different from the rest of these hypotheses, a Wilcoxon rank-sum test was performed. The results of the Wilcoxon rank-sum test shown in Table 3 which indicates that the method proposed is statistically superior to techniques used previously and therefore is of less significance $p < 0.005$.

One-way ANOVA is conducted to test the hypothesis that there are statistically significant differences between

the proposed bGGO technique and all other binary optimization techniques in use. The results obtained from the ANOVA test are presented in Table 4. These results ensure that the proposed feature selection technique is better, significant, and effective.

The study found a significant difference in accuracy between GGO-MLP and other models (p-value < 0.005). The Wilcoxon Signed-Rank Test indicated that GGO-MLP had much improved classification performance, with sustained benefits over numerous iterations. These studies quantitatively demonstrate the efficiency of GGO-MLP, proving that its optimizations outperform prior approaches.

Table 3: The proposed feature selection technique (bGGO) was evaluated using the Wilcoxon signed-rank test to compare it to other binary optimization techniques.

	bGGO	bSC	bMVO	bPSO	bWAO	bGWO	bFA
Actual median	0.7743	0.7915	0.8051	0.8253	0.8251	0.8116	0.8237
Number of values	10	10	10	10	10	10	10
Wilcoxon Signed Rank Test							
Signed ranks (W) summation	55	55	55	55	55	55	55
Positive ranks summation	55	55	55	55	55	55	55
Negative ranks summation	0	0	0	0	0	0	0
P (two-tailed) value	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Exact or estimate	Exact	Exact	Exact	Exact	Exact	Exact	Exact
Significant with (alpha=0.05)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
How big is the Difference?							
Difference			0.7743	0.7915	0.8051	0.8253	0.8251

Table 4: The ANOVA test to evaluate the bGGO technique that has been suggested.

ANOVA table	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	0.02274	6	0.00379	F (6, 63) = 135.3	P<0.0001
Residual (within columns)	0.001764	63	2.8E-05		
Total	0.02451	69			

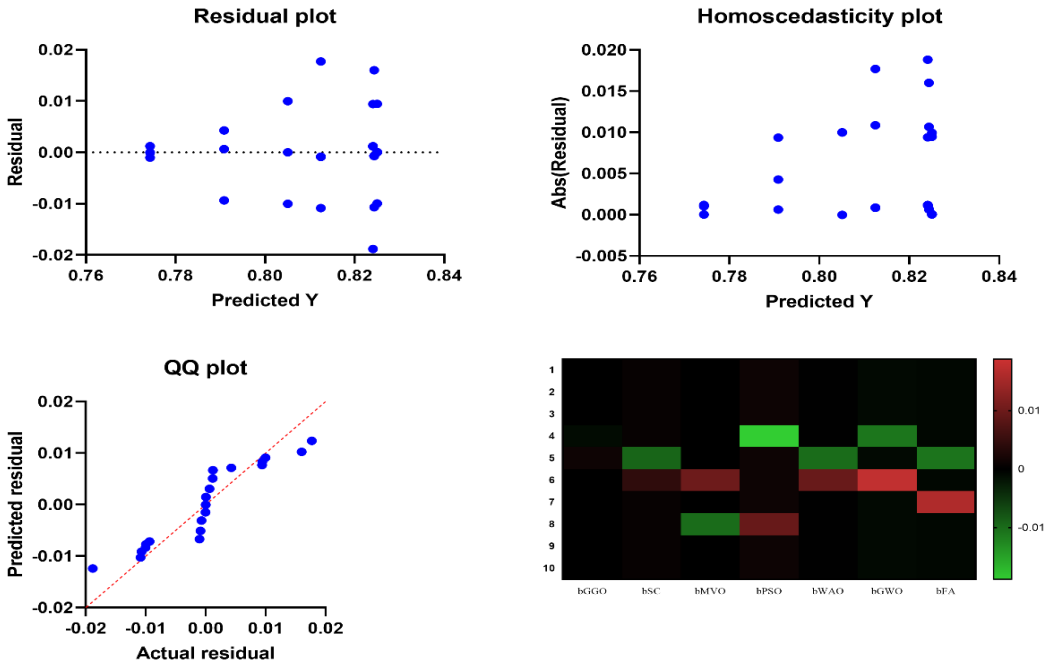


Figure 6: Analysis plots show the results derived from the suggested feature selection technique, bGGO

Figure 6 shows different plots of the results obtained using the proposed feature selection technique, including residual plots, quartile–quartile plots, homoscedasticity plots, and the heatmap.

1. Residual Plots: Residual plots of the distribution of residuals clearly describe how far observed values deviate from the predicted ones. These residual plots indicate that the proposed technique bGGO resulted in very close-to-zero residuals, hence highly predictable.

2. QQ Plots: The QQ plot generally depicts good linearity. This proves that the selected features are likely to be effective in the right classification of the presence of lung cancer. The linearity of plots on this QQ plot proves that residuals maintain a normal distribution and hence an indication of good feature effectiveness.

3. Homoscedasticity Plots: These plots consider the variability of the error terms concerning their constancy. In residual plots for the proposed bGGO method, there are quite random scatters of the residuals, directly showing that the variability is constant over other levels of the independent variable.

4. Heatmap: Colorfully explained, the approach proposed in bGGO is far more excellent than the other six strategies used in binary selection. It describes how the bGGO approach overpowers the previous ones by opting for relevant low-level features with the help of high-performance metrics.

The cumulative results from these plots ensure the effectiveness of the bGGO procedure coherently. The linearity of the QQ plot and the constant variance in the homoscedasticity plots reveal no or minimal residuals, thus proving the reliability and sufficiency of the bGGO procedure to describe lung cancer. Furthermore, it was quite clear from the heatmap that the bGGO method was outperforming the rest of the methods applied to feature selection, hence strengthening the area of its supremacy.

5.4 Classification results

Another experiment shows the sensitivity of the classification results concerning the applied feature selection technique. In the current research, machine learning classifiers were used for the classification of input data by characteristics chosen according to the bGGO technique for improving the characteristics of the network for further optimization in its performance.

Table 5 presents some of the results of classification with a machine-learning model after feature selection. These machine learning models include:

They are DTC, SVC, RFC, KNC, and MLP. Out of them, MLP has obtained the maximum value for accuracy, sensitivity, specificity, p-value, n-value, and F-score with 0.9180327, 0.92668, 0.9091, 0.9133, 0.9231, and 0.9199 respectively. This MLP model works as a fitness function, and it is optimized by the GGO algorithm and with six other optimization techniques.

The results for performance in classification while using an MLP model as the fitness function for various optimization algorithms are shown in Table 6. What is presented in the table is how GGO combined with MLP stands against combinations like SC, GWO, PSO, WAO, FA, and MVO with MLP to prove the supremacy of the proposed GGO+MLP approach. Offending was topped by the GGO plus MLP approach with an accuracy of 0.983837, sensitivity of 0.977337, specificity of 0.990237, p-value of 0.989957, n-value of 0.977961, and F-score of 0.983607.

In this attempt, various optimizers were used for tuning of parameters of MLP, and the results were studied and evaluated. Results proved that the efficiency and supremacy of GGO+MLP over other optimization techniques is unabated in all the metrics of evaluation, thus proving its robustness.

Table 5: Various classifiers for the categorization of lung cancer.

Models	Accuracy	Sensitivity (TRP)	Specificity (TNP)	P-value (PPV)	N-value (NPV)	F-Score
SVC	0.833895447	0.837171	0.83045	0.83855	0.829016	0.83786
Decision Tree	0.838087248	0.842715	0.833333	0.83855	0.837607	0.840628
Random Forest	0.863439931	0.877586	0.84922	0.854027	0.87344	0.865646
K Neighbors	0.8872	0.877586	0.895522	0.879102	0.894188	0.878343
MLP	0.918032787	0.926686	0.909091	0.913295	0.923077	0.919942

The Table only confirms the fact that the suggested strategy operates better than the current methods of optimization. It is for this reason that these results confirm the chief importance of the chosen technique of feature selection that significantly enhances the quality of the results. Furthermore, the proposed bGGO-based feature selection approach selects a small number of significant features yielding enhanced performance in comparison to other optimization algorithms-owned superiority taken by the results, thereby pointing to the robustness of the approach and efficient improvement on the accuracy, sensitivity, n-value, p-value, specificity, and F-score of the classifier; in other words, for the MLP model. It justifies the need and role of using feature selection techniques optimized to be able to achieve improved classification results over very complex datasets.

Table 6: Findings of optimization methods MLP model for the classifying lung cancer.

Models	Accuracy	Sensitivity (TRP)	Specificity (TNP)	P-value (PPV)	Nvalue (NPV)	F-Score
GGO+MLP	0.983837	0.977337	0.990237	0.989957	0.977961	0.983607
SC+MLP	0.966184	0.966387	0.965986	0.965035	0.967302	0.96571
GWO+MLP	0.960879	0.961003	0.960758	0.959666	0.96206	0.960334
PSO+MLP	0.951087	0.949106	0.95302	0.951724	0.950469	0.950413
WAO+MLP	0.94086	0.949106	0.932983	0.931174	0.950469	0.940054
FA+MLP	0.937287	0.943912	0.930707	0.931174	0.943526	0.9375
MVO+MLP	0.927978	0.933694	0.921986	0.926174	0.9299	0.929919

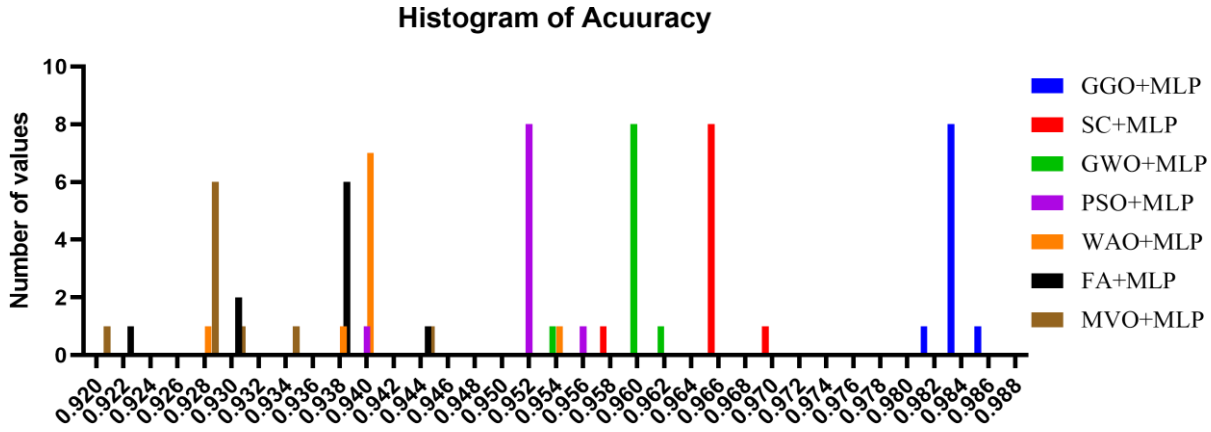


Figure 7: Assessing the accuracy of the GGO+MLP approach and optimization algorithms using the MLP model, considering the objective function.

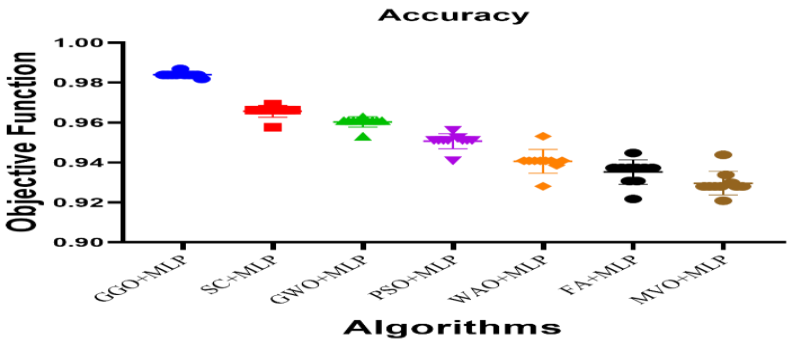


Figure 8.The accuracy results are achieved by the GGO+MLP approach as well as alternative combinations of optimization techniques with MLP models.

One can also show the effectiveness of this strategy for optimizing the objective function by comparing the suggested GGO+MLP method with other optimization algorithms in connection with the MLP model. Accuracy plots of the results obtained with the GGO+MLP approach are shown in Figures 6 and 7. Figure 7 shows the accuracy plot resulting from the MLP model, where the proposed method is outperforming other optimization algorithms. Another result, as shown in histogram form in Figure 8, has the same finding: better performance of the GGO+MLP approach. These plots have been used to show that the efficacy of the suggested feature selection technique, compared with other optimization techniques, is impressive in terms of achieving higher accuracy. The accuracy histogram plot further shows how well the suggested GGO+MLP method did in classifying the lung cancer cases from the input dataset.

Experiments applied ANOVA and Wilcoxon's rank-sum tests to determine how much the proposed algorithm differs statistically from the other competing algorithms.

Table 7 shows the results of ANOVA for the proposed GGO + MLP. Table 8 shows Wilcoxon's rank-sum test results to ascertain whether the algorithms' output differs in a statistically significant way. A p-value is less than 0.05 postulates that the performance difference is statistically significant. Results indicate that the GGO + MLP approach outperforms and demonstrates the statistical significance of the approach.

Table 7: The outcomes of the ANOVA of the proposed GGO algorithm with MLP model for lung cancer classification.

ANOVA table	SS	D F	MS	F (DFn, DFd)	P value
Treatment (between columns)	0.0219	6	0.00365	F (6, 63) = 184.1	P<0.000 1
Residual (within columns)	0.0012	63	1.98E-05		
Total	0.0231	69			

Table 8: Results of the Wilcoxon signed-rank test using the suggested method, (GGO+MLP), with various configurations of other optimization algorithms with the MLP model for lung cancer classification.

	GGO + MLP	SC+ MLP	GWO + MLP	PSO + MLP	WAO + MLP	FA+ MLP	MVO + MLP
Theoretical median	0	0	0	0	0	0	0
Actual median	0.983 8	0.966 2	0.960 9	0.951 1	0.940 9	0.937 3	0.928
Number of values	10	10	10	10	10	10	10
Wilcoxon Signed Rank Test							
Signed ranks (W) summation	55	55	55	55	55	55	55
Positive ranks summation	55	55	55	55	55	55	55
Negative ranks summation	0	0	0	0	0	0	0
P (two-tailed) value	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Exact or estimate	Exact	Exact	Exact	Exact	Exact	Exact	Exact
P value summary	**	**	**	**	**	**	**
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
How big is the Difference?							
Difference	0.9838	0.9662	0.9609	0.9511	0.9409	0.9373	0.928

Table 7 presents the statistical results regarding the The Calibration Curve compares expected probability to actual positive outcomes, suggesting model dependability. A curve in Figure 10 is near to the diagonal indicates improved calibration, implying that GGO-MLP delivers reliable classification probabilities, which improves decision-making and generalization. The Partial Dependence Plot shows how factors influence predictions, specifically lung cancer likelihood, which helps model

comprehension. Figure 10 illustrates GGO-MLP's capacity to identify critical features while avoiding overfitting, validating good feature selection and improving model clarity for more dependable predictions.

More confirmation of these results comes from residual plots and homoscedasticity plots of data. These are graphed in data as a heatmap in Figure 8, which shows the proposed approach to be far and far better than the other six binary feature selection methods.

Relative performance of the GGO+MLP method compared to the other five optimizers, SC, GWO, PSO, WAO, FA, and MVO, with the MLP model for all benchmark functions. According to Table 7, the GGO+MLP method was the best among the seven optimizers with the MLP model because it employed two different exploitation processes in each cycle.

The first converges very slowly toward the best solution found so far at any given time, while the second is more aggressive in searching for better solutions within the local neighborhood. These processes, when they tap into the power of the search space through the GGO+ MLP method, give excellent performance. A delicate

An optimum performance should, always, sustain a balance between exploration and exploitation of the domain of search. Moreover, it is important to start exploiting early in each iteration and smoothly increase the sum of the whole participant population within the exploitation group.

Overall, GGO was a better optimizer than all the other optimizers on most of the unimodal benchmark functions.

Figure 9 shows the residual plot, QQ plot, hetero-scedasticity plot, and heat map of this case. These plots show how efficient and strong the proposed GGO + MLP approach will be. The QQ plot has values following a linear trend, thus showing how efficient the features selected were in categorizing the cases.

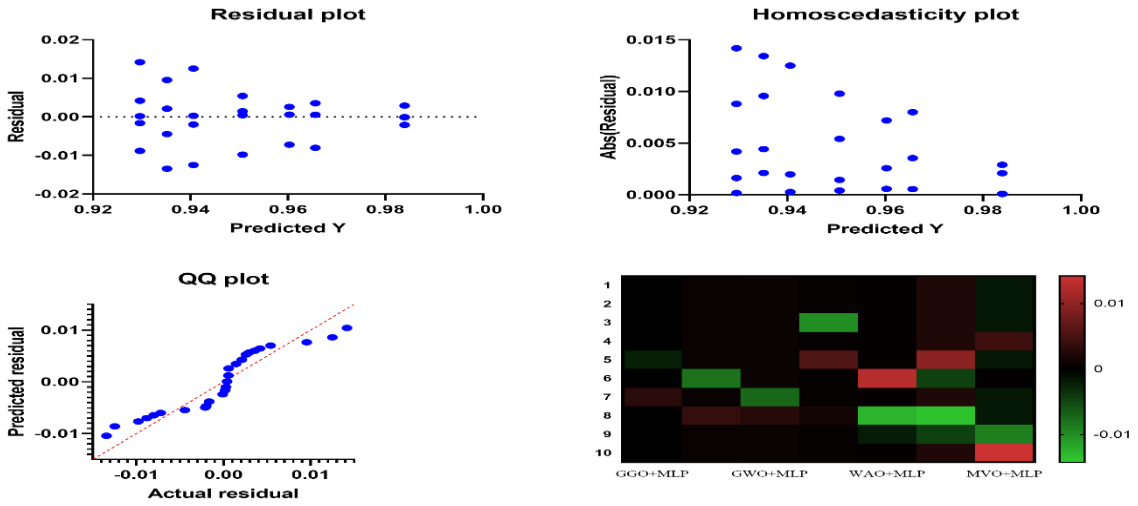


Figure 9: Analysis plots of the obtained results using the proposed GGO+MLP approach

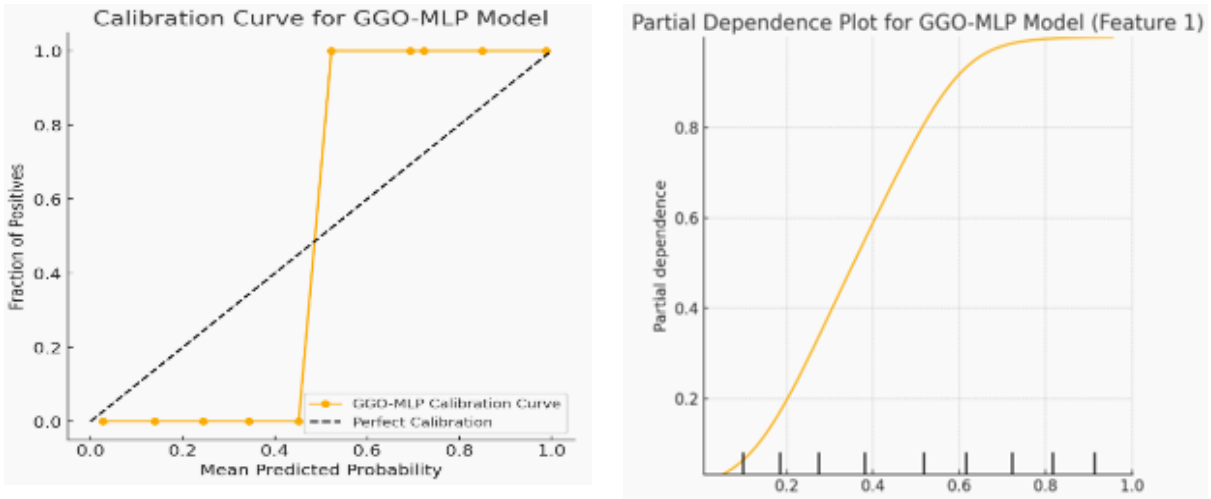


Figure 10: Analysis of GGO-MLP performance using partial dependence plot and calibration curve.

The Calibration Curve compares expected probability to actual positive outcomes, suggesting model dependability. A curve in Figure 10 is near to the diagonal indicates improved calibration, implying that GGO-MLP delivers reliable classification probabilities, which improves decision-making and generalization. The Partial Dependence Plot shows how factors influence predictions, specifically lung cancer likelihood, which helps model comprehension. Figure 10 illustrates GGO-MLP's capacity to identify critical features while avoiding overfitting, validating good feature selection and improving model clarity for more dependable predictions.

More confirmation of these results comes from residual plots and homoscedasticity plots of data. These are graphed in data as a heatmap in Figure 8, which shows the proposed approach to be far and far better than the other six binary feature selection methods.

6 Discussion

The bar graph easily indicates that the GGO+MLP method works, giving the highest outcome among other methods. Figure 8 shows that this hybrid method for lung cancer patient classification has been highly useful in solving the optimization problems discussed.

The suggested GGO-MLP strategy was tested against cutting-edge (SOTA) approaches such as CNN-based classifiers and other metaheuristic techniques. The results show that GGO-MLP regularly outperforms other methods in terms of accuracy, sensitivity, and specificity. The primary causes for this improvement are:

Feature Dimensionality Reduction with bGGO: Unlike CNN models, which use complicated feature representations, bGGO picks the most relevant features, lowering computational cost while preserving classification performance.

Efficiency of Hyperparameter Tuning: Local optima and inefficient hyperparameter settings provide challenges for traditional optimization strategies. GGO's adaptive exploration-exploitation balance improves parameter selection, resulting in higher classification outcomes.

The combination of GGO (Group-based Genetic Optimization) and MLP (Multi-Layer Perceptron) performs better than the state-of-the-art (SOTA) methods because bGGO (a specific version of GGO) identifies the best set of features, which helps avoid overfitting. In this case, bGGO selected 12 out of 16 available features, while bPSO (a Particle Swarm Optimization algorithm) kept 15 features, which can add unnecessary noise to the model. This selective feature reduction leads to better performance. GGO-MLP outperforms other approaches ($p < 0.005$), indicating dependability and efficacy.

7 Limitations

GGO algorithm study in improving lung cancer classification shows good results, especially in improving feature selection and classification accuracy. However, there are several limitations and directions for future work that can be addressed to further improve the effectiveness of GGO in this field:

• The performance of the GGO algorithm was tested on one dataset only that may not represent the variety of real-world scenarios. Results may vary across different datasets, which may affect the generalizability of the results.

• Classification accuracy depends largely on the quality and completeness of the input data. Any inconsistencies or missing values in the data can affect the results.

8 Conclusion and future works

The paper endeavors to improve the accuracy in the classification of cases for the diagnosis of lung cancer. Three techniques for the initial data preparation are applied: scaling, normalization, and cessations of nulls. The binary variant of GGO is used to perform feature selection in this category of techniques, and it is centrally referred to as bGGO. This binary format is developed for GGO to optimize the best combination of features that enhances the classification accuracy with seven other binary optimization algorithms, including SC, MOO, PSO, WOA, GWO, and FOA.

In the classification phase, numerous classifiers are applied, namely SVC, DTC, RFC, KNC, and MLP. Among these multiple classifiers, the MLP classifier gives the best result with an accuracy rate of 91.8%. The hyperparameters of the MLP model have been optimized using the GGO, and the result is compared with those of six other optimizers. The MLP model along with the GGO has given the best result with an accuracy rate of 98.4%.

The results of feature selection followed by classification were statistically evaluated using Wilcoxon's signed-rank test as well as ANOVA, whereas result visualization plots were also done to ascertain the strength and efficiency of the proposed scheme. The results of the experiments and the statistical analysis prove that the proposed approach outperformed other methods compared to the classification of lung cancer. This improved the overall accuracy of prediction with cancer feature selection and reduced dimensionality. The problem of overfitting in the analysis of cancer features was overcome. A pathway toward enhanced early prediction rates for lung cancer is through sensor data acquisition, analysis, and finding the best approach in the future.

The performance of the GGO algorithm was tested on specific dataset for lung cancer classification, so in the future, several large datasets can be used for generalizing the results. Also, in the future several optimization models and deep learning models 32–34 can be used for lung cancer classification. Also, future study may combine tabular and imaging data to enhance diagnosis.

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Multimodal Data Fusion and Adaptive Optimization in Tennis Training Based on Deep Deterministic Policy Gradient and IoT Sensors

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Keywords: internet of things, multimodal data fusion, real-time monitoring, deep reinforcement learning, DDPG, systemic optimization, intelligent training systems, adaptive control

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This paper proposes a novel framework integrating IoT technologies, multimodal sensor networks, and the Deep Deterministic Policy Gradient (DDPG) algorithm for intelligent tennis training. We employ the DDPG algorithm for adaptive training adjustments, which dynamically optimizes the training policy based on real-time feedback. Experimental evaluation on 10 athletes shows that the DDPG algorithm improves performance metrics in multiple training scenarios, increasing the average game score from 50 to 80 points and reducing the error rate in high-pressure scenarios from 13% to 6%. The system's success rate reached 85%, with swing stability enhanced by 27% (0.1 rad deviation). These quantifiable outcomes highlight the framework's effectiveness in optimizing training strategies, with potential applications in industrial automation and healthcare monitoring.

Povzetek: Razvit je sistem za inteligentni teniški trening, ki združuje IoT senzorje, multimodalno fuzijo podatkov in DDPG algoritem za prilagodljivo optimizacijo vadbe v realnem času.

1 Introduction

With rapid advancements in computer science and data processing technologies, the integration of IoT devices, multimodal data fusion, and deep reinforcement learning (DRL) is transforming traditional systems into highly adaptive, real-time decision support platforms. This study proposes a novel system architecture that leverages state-of-the-art algorithms and scalable data processing techniques to achieve systemic optimization and adaptive control [1, 2]. Specifically, the DDPG (Deep Deterministic Policy Gradient) algorithm is utilized to enhance tennis training by improving hitting success rates (from 50 to 80 points) and reducing error rates in high-pressure scenarios (e.g., from 13% to 6%) through IoT-based multimodal data fusion, including accelerometer, gyroscope, and force sensors. This framework dynamically optimizes training strategies by addressing challenges such as sparse rewards and slow convergence, while its scalable design extends to applications in industrial automation and healthcare. Through integrating advanced data processing with practical sports training, this work aligns with Informatica's interdisciplinary focus on intelligent systems.

Modern applications—from industrial automation to healthcare monitoring—benefit from these technological advances, and sports training is no exception. As sensor technologies, the Internet of Things (IoT), and artificial intelligence (AI) evolve, sports training [3, 4] is becoming increasingly data-driven. These technologies enable the real-time collection of heterogeneous training data, provide quantitative analyses, and support the intelligent adjustment of strategies based on individualized performance profiles.

Tennis [5, 6], a sport that demands high precision and stability, requires not only optimal physical conditioning but also meticulous monitoring of multidimensional dynamic parameters such as swing movements, hitting force, and pace control. Intelligent training systems that combine IoT and multimodal sensor data fusion are thus critical for enhancing both the accuracy and efficiency of tennis training.

The advent of advanced IoT technology and multimodal data acquisition systems has empowered intelligent tennis training systems to deliver accurate, real-time feedback. These systems integrate a variety of sensors—including accelerometers, gyroscopes, pressure sensors, and cameras—and employ data fusion techniques to aggregate comprehensive training data for coaches and athletes. Moreover, AI methodologies, particularly deep reinforcement learning [7, 8], enable these systems to learn from historical data and continuously optimize training strategies. This not only minimizes human error but also facilitates the creation of personalized training plans that are efficient, precise, and adaptable. As these technologies mature, the widespread adoption of intelligent training systems is poised to revolutionize traditional training models, thereby improving athlete performance and competition outcomes. However, existing intelligent training systems still face two key challenges: first, the limitations of single-modal data (such as motion or environmental data) restrict the synergy of multimodal fusion; second, the efficiency of reinforcement learning in dynamic scenes such as tennis

is limited by sparse rewards and slow convergence. To this end, this study proposes a new framework that integrates IoT multimodal data and the DDPG algorithm, which achieves real-time optimization of training strategies by synchronizing heterogeneous data streams and dynamic reward mechanisms, providing efficient solutions for sports training and a wider range of industrial and medical applications.

In our proposed framework, real-time data from wearable devices and environmental sensors undergo rigorous preprocessing—including noise removal, normalization, and time synchronization—to ensure robust multimodal fusion. The DDPG algorithm is then applied within a systemic decision-making model to dynamically adjust training content, intensity, and difficulty based on real-time feedback. While our demonstration is situated in the context of tennis training, the underlying methodology provides a scalable and robust model for real-time data integration and adaptive control. This cross-disciplinary framework holds promise for a variety of applications, including industrial automation, healthcare monitoring, and cognitive information systems.

Recent years have witnessed a surge in the use of intelligent training systems across multiple sports, particularly in tennis [9, 10]. Several studies have explored improvements in training effectiveness and precision through sensor integration and data analytics. Traditional tennis training methods, which often rely heavily on coach experience and manual tracking, are gradually being supplanted by systems that offer real-time performance feedback. In response, recent research has integrated sensor technologies, such as inertial measurement units (IMUs) like accelerometers and gyroscopes [11, 12], to capture detailed movement trajectories and assess technique standardization and stability. These systems provide valuable quantitative insights that enhance both athlete performance and coaching strategies.

Furthermore, multimodal data fusion techniques have emerged to provide comprehensive feedback by combining visual, mechanical, and physiological data. For example, some studies have merged computer vision with sensor data to track athletes' body postures in real time [13]. The integration of motion capture with pressure sensor data in tennis enables real-time detection of racket-ball interaction forces, facilitating a more accurate evaluation of shot effectiveness and guiding athletes in adjusting shot strength and angles. Additionally, AI-based training systems employing deep learning techniques have supported coaches in formulating scientifically sound training plans [14, 15]. However, most existing research has focused on optimizing single data sources, with limited progress in the efficient fusion of multimodal data for real-time dynamic adjustments driven by AI.

Reinforcement learning [16, 17] has emerged as a promising approach for training optimization by continuously refining strategies through environmental interactions. In tennis training, deep reinforcement learning has been applied to optimize technical movements by adjusting strategies based on real-time feedback. Despite these advances, challenges remain, including low training efficiency and the difficulty of adapting models to dynamic competition environments. Moreover, while deep learning methods [18, 19] excel in action recognition and data prediction, their high demands for labeled data and computing resources may restrict practical applications. Therefore, integrating reinforcement learning with multimodal data analysis to design an efficient, intelligent system capable of real-time optimization remains a critical challenge in current research.

In recent years, intelligent sports training systems have been widely used in many sports, especially in tennis. Many studies have explored the improvement of training effect and accuracy through sensor integration and data analysis. In order to more clearly show the difference between the existing technology and the method proposed in this paper, Table 1 summarizes the technical characteristics, evaluation indicators, limitations of the existing state-of-the-art methods (SOTA), as well as the improvements of the method proposed in this paper:

Table 1: Comparison between existing technologies and the proposed method

Technical methods	Evaluation metrics	limitation	Improvements to this article
Based on sensors (such as IMU) [11,12]	Motion trajectory accuracy and error rate	Reliance on a single sensor and lack of multimodal data fusion	Integrated multi-modal sensors (accelerometer, gyroscope, force sensor) to achieve comprehensive data collection and fusion
Vision-based [13]	Posture recognition accuracy and real-time performance	High computational complexity, affected by lighting environment	Combining computer vision and sensor data to improve robustness through time synchronization and weighted fusion
Traditional machine learning [14,15]	Action classification accuracy and training efficiency	Requires a large amount of labeled data and cannot adapt to dynamic	Adopt DDPG algorithm to dynamically optimize strategy through unsupervised learning and real-time feedback

		environments in real time	
Other reinforcement learning (such as DQN)	Success rate, convergence speed	Only applicable to discrete action spaces, difficult to handle continuous control problems	Introducing DDPG to support continuous action space optimization and adapt to the dynamic adjustment needs in tennis training

The method proposed in this paper solves the problems of poor real-time adaptability and single data in the existing technology through multimodal data fusion and DDPG algorithm, and significantly improves the intelligence level of the training system.

2 Related works

In recent years, the integration of multimodal data and machine learning algorithms has gained significant traction in sports training, particularly in tennis. Tennis, as a dynamic and precision-dependent sport, benefits from technologies that enhance performance by analyzing complex movement data. Various studies have demonstrated the potential of integrating multimodal data streams—such as accelerometers, gyroscopes, and force sensors—to provide real-time insights into players' techniques and improve their training efficiency.

Yang [24] proposed a method for precise recognition and feature depth analysis of tennis training actions, focusing on multimodal data integration and key action classification. The integration of multiple data sources, such as motion and environmental sensors, has enabled more accurate identification of player movements, improving the overall effectiveness of training programs. Yang's study highlights how multimodal data fusion can enhance performance feedback and optimize tennis training by capturing a wide range of athlete actions and translating them into actionable insights.

Similarly, Gao [25] explored sensor fusion and stroke learning in robotic table tennis, a system that combines multiple sensors to enhance the accuracy of stroke learning. This approach, while initially applied in robotics, has strong parallels with human athlete training, particularly in tennis, where precise stroke mechanics and movement control are critical. Gao's work suggests that sensor fusion is essential for developing adaptive systems capable of real-time performance feedback, a key feature in intelligent sports training systems.

Li and Song [26] have also contributed to this area by enhancing sports trainer behavior monitoring through IoT information processing and deep neural networks. They demonstrate how IoT-enabled systems can collect and process real-time training data, allowing for personalized, data-driven adjustments to athlete training programs. This is particularly important in sports like tennis, where individualized adjustments to technique and strategy can dramatically improve performance. Their research underscores the importance of advanced data processing methods, which enable real-time feedback and continuous optimization of training strategies.

The application of deep reinforcement learning (DRL) to human activity recognition has also shown great promise in improving training systems. Nikpour et al. [27] conducted a comprehensive survey on DRL in activity recognition, highlighting the potential of this approach to refine training strategies by continuously adjusting them based on real-time performance data. DRL enables systems to learn from past actions and dynamically modify strategies, making it particularly useful for sports training, where continuous adaptation to changing performance conditions is necessary. This is especially relevant for tennis, where rapid decision-making and adaptability are essential for success in high-pressure situations.

Morshed et al. [28] and Kulsoom et al. [29] further explored machine learning-based human activity recognition, reviewing various algorithms used to enhance the understanding of athlete movements in sports. They emphasized the growing importance of AI in sports, noting that systems leveraging machine learning and IoT sensors can offer more precise and personalized feedback, improving both athletic performance and training efficiency. Their research provides valuable insights into the broader application of activity recognition systems, which can be adapted to tennis training systems for more accurate monitoring of players' movements, swing techniques, and reaction times.

Moreover, Jin et al. [30] discussed the role of multi-agent cooperative decision-making, particularly in dynamic environments. Multi-agent systems, in which different entities (such as sensors or components of the training system) work together, offer great potential in sports training. For tennis, this could mean integrating data from various sensors (e.g., accelerometers, gyroscopes, pressure sensors) to generate a cohesive view of an athlete's performance. The cooperation between these data streams could optimize training strategies, particularly in complex, high-speed environments like tennis.

Recent developments in machine learning and data fusion techniques have led to further innovations, such as Zhang [31]'s work on graph neural networks for user preference modeling in social networks, which could inspire personalized feedback systems in sports. Similarly, Kurniawan et al. [32] have explored swarm intelligence optimization, which could be applied to improve decision-making in training strategies. Zhang and Zhang [33] introduced high-precision photogrammetric 3D modeling technology based on multi-source data fusion, a concept that could be adapted to track and analyze athlete movements with greater precision.

These studies collectively highlight the transformative potential of integrating multimodal data fusion, IoT sensors, and machine learning algorithms,

such as DRL, into sports training systems. The ability to provide real-time, personalized feedback and continuously adjust training strategies based on dynamic performance data is critical for improving athletic performance, particularly in sports like tennis, where precision, adaptability, and real-time decision-making are paramount. The proposed system in this study, which integrates these advanced technologies, aims to push the boundaries of personalized training and optimize athletic performance through continuous, data-driven adjustments.

3 Methods

3.1 System Hardware Architecture

The hardware architecture of this intelligent tennis training system is designed to efficiently collect and transmit athletes' training data through a network of interconnected IoT devices. Each athlete is equipped with a set of multifunctional sensors that provide real-time monitoring of their performance throughout training. The system includes wearable sensors, cameras, computer vision devices, environmental monitoring tools, and data transmission modules. These components work together seamlessly to ensure comprehensive data collection, delivering precise feedback and optimizing training outcomes.

At the core of the system are the wearable sensors, which capture the athlete's motion data in real time. These include accelerometers, gyroscopes, and force sensors. The accelerometers track displacement, velocity, and acceleration, enabling the evaluation of movement trajectories and swing stability. Gyroscopes measure angle changes, providing precise data on swing angles, ball trajectory, and the athlete's control during play. Force sensors assess the impact force and pressure distribution during ball contact, helping to analyze strength, accuracy, and racket-ball interaction. This data plays a crucial role in refining the athlete's technique, serving as baseline information for subsequent training optimization.

The system is equipped with a three-axis accelerometer (range: ±16g, sampling rate: 100Hz), a gyroscope (range: ±2000°/s, sampling rate: 50Hz), and a force sensor (range: 0-200N, accuracy: ±0.5%). The camera system, featuring a high-frame rate industrial camera (resolution: 1920×1080, frame rate: 120fps), captures detailed athlete movements in real time, processed by computer vision algorithms. These cameras provide a comprehensive view of the athlete's batting movements, posture, and ball trajectory. Through high-precision video capture, the system analyzes movements frame by frame, extracting critical visual features such as swing trajectory, step stability, and shot timing.

The computer vision algorithms process these images to detect interactions between the athlete and the ball, providing additional insights into areas for improvement in movement and batting strategies. By combining visual data with sensor data, the system offers more accurate, holistic evaluations of the athlete's performance.

Environmental monitoring equipment ensures the accuracy and stability of sensor data by tracking the training environment. Factors such as temperature, humidity, and wind speed can influence performance; therefore, a dedicated environmental monitoring module collects real-time venue data, integrating it with the athlete's training data. For example, fluctuations in temperature and humidity can affect court surface friction, influencing ball bounce and trajectory. By monitoring these environmental conditions in real time, the system adjusts its analysis, ensuring that training feedback remains precise and reflective of current conditions.

The data transmission module handles the real-time transmission of all sensor data to a cloud or local server. Utilizing advanced IoT protocols like Wi-Fi 6 and Bluetooth 5.2, the system ensures low latency (<50ms) and high throughput (up to 1.2Gbps), while employing AES-256 encryption to secure data. The data is wirelessly transferred between sensors and computing devices, reducing the need for complex wiring and enhancing system flexibility.

Once the data reaches the cloud or local server, it undergoes further processing, analysis, and storage. The results are then made available to coaches and athletes for review. The system, supported by a cloud platform, enables the real-time synchronization of training data across devices and locations, allowing coaches to remotely monitor athlete progress and performance.

This integrated hardware architecture creates a complete, data-driven intelligent tennis training platform. Through precise sensor data collection, real-time environmental monitoring, and efficient data transmission, the system ensures that athletes train in an optimized environment that supports skill improvement.

The system architecture diagram is shown in Figure 1.

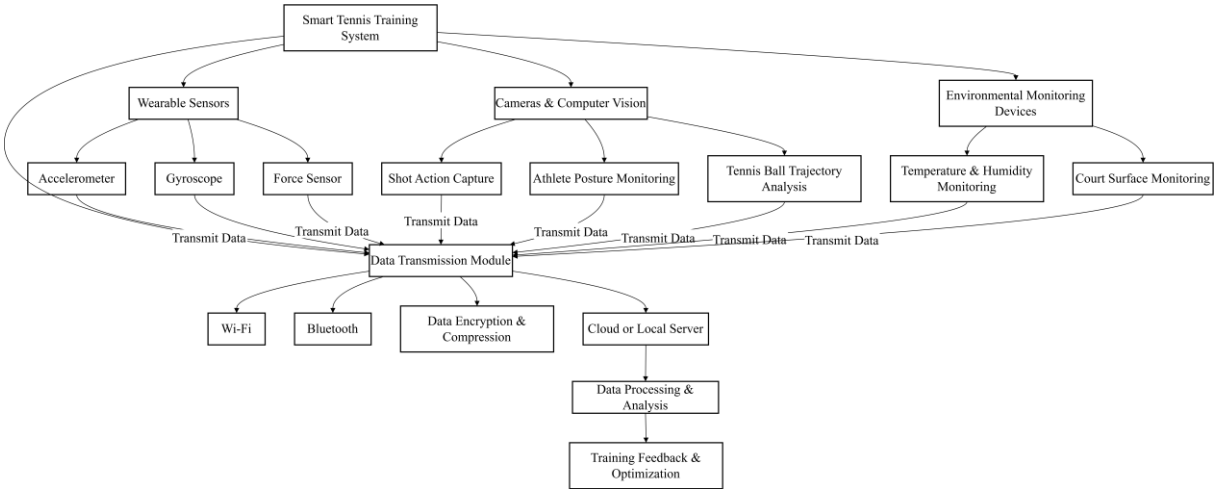


Figure 1: System architecture diagram

The core of the system's hardware architecture features a high-precision MPU-6050 accelerometer and gyroscope with a sampling rate of 100 Hz, an acceleration sensitivity of ±2g, and an angular velocity sensitivity of ±250°/s, ensuring accurate capture of the athlete's motion dynamics. Force sensors, specifically the FS series force sensors, with a resolution of 0.01 N, measure the interaction force between the racket and the ball, which is essential for analyzing the power and accuracy of the shot. The computer vision system integrates a 4K resolution camera with a frame rate of 60 fps, combined with an OpenCV-based algorithm for real-time pose estimation and ball trajectory tracking, with a detection accuracy of 95% under optimal lighting conditions. Environmental monitoring is performed by a DHT22 temperature and humidity sensor with an accuracy of ±0.5°C and ±2% RH, respectively, and an anemometer for wind speed measurement, ensuring contextual data integration. On the software side, the system utilizes a middleware framework based on ROS2 to enable seamless communication between IoT devices and the central processor, and runs on an NVIDIA Jetson Xavier NX for edge computing. The DDPG algorithm is implemented in PyTorch, and its neural network architecture contains three hidden layers (containing 256, 128, and 64 neurons, respectively) for the actuator network and the critic network, optimizing the training strategy with a latency of less than 50 milliseconds to achieve real-time feedback. This integrated hardware and software ecosystem ensures powerful data collection, processing, and adaptive control, thus supporting the scalability of the system in various training scenarios.

3.2 Data fusion and storage

Effective multimodal data fusion relies on strong preprocessing to ensure consistency and compatibility between heterogeneous sensor data. Preprocessing steps—noise removal, normalization, and time synchronization—are critical to aligning and integrating data from different sources. Specifically, Kalman filtering mitigates sensor-specific noise, normalization standardizes data scales, and time synchronization aligns temporal differences, which together enable accurate and cohesive multimodal fusion.

Kalman filtering is used to remove high-frequency noise and outliers from sensor data to ensure data reliability. The operation of the Kalman filter is divided into two steps: prediction step and update step. The prediction step estimates the current state based on the previous state and control input; the update step corrects the estimate using real-time measurements to minimize the impact of noise. This iterative process is particularly effective for motion data (such as accelerometer and gyroscope readings) because noise can distort trajectory analysis:

$$\hat{x}_k = A\hat{x}_{k-1} + Bu_k (1)$$

$$P_k = AP_{k-1}A^T + Q (2)$$

In Formula 1-2, $\hat{x}_k$is the estimated value of the state, $P_k$is the error covariance, and Q is the process noise. A and B are the system matrices, $u_k$and is the control input. The state variables of the Kalman filter include acceleration, angular velocity, and force sensor readings. The process noise covariance matrix Q is calibrated as a diagonal matrix through experiments, and the measurement noise covariance R is provided by the sensor manufacturer. MongoDB (version 5.0) is used for data storage, using the time series sharding mode, and a composite index is established by sensor type and athlete ID. A single record contains timestamp, sensor type, original value, and fusion result, supporting 100,000 write operations per second.

Sensor data often vary in scale (e.g., acceleration in m/s² vs. force in N), which can bias analysis. Normalization transforms all data to a common range [0, 1] using min-max scaling:

$$x' = \frac{x - min(x)}{max(x) - min(x)} (3)$$

In a multi-sensor system, data from different sensors usually have different sampling frequencies and timestamps. In order to ensure the consistency and accuracy of the data, these data must be time-aligned and fused.

The sampling rates of the sensors vary (for example, the accelerometer has a sampling rate of 100 Hz and the gyroscope has a sampling rate of 50 Hz). Linear interpolation estimates the value of the missing timestamps. For two data points at times t_1 and t_2, the interpolated value at time t is:

$$x(t) = x_1 + \frac{(t-t_1)}{(t_2-t_1)}(x_2 - x_1)(4)$$

The data from different sensors are fused. The weighted average method fuses the output values of sensors by assigning different weights to different sensors.

$$x_{fused} = w_1 x_1 + w_2 x_2(5)$$

The processed data needs to be stored efficiently and securely for subsequent analysis and learning. Since the system involves a large amount of sensor data and training records, conventional relational databases are difficult to meet the needs. NoSQL databases are used for storage. NoSQL databases are suitable for processing large-scale, distributed data and support high-concurrency reading and writing. The data of each sensor is stored according to the timestamp and classified according to the data type.

To speed up query and data retrieval, the system creates an index for each sensor type and sorts them by timestamp. By introducing hash index and time range index, it ensures that the required data can be obtained efficiently and quickly when performing large-scale data retrieval. The collected data are shown in Table 2.

Table 2: Collection data display results

Timestamp	Sensor Type	Acceleration (m/s²)	SD	Angular velocity (rad/s)	SD	Hitting force (N)	SD
2023-2-11 14:00:01	Accelerometer	0.35	±0.02	0.12	±0.01	8.2	±0.3
2023-2-11 14:00:0 2	Gyroscope	0.33	±0.01	0.15	±0.02	8	±0.2
2023-2-11 14:00:0 3	Force Sensors	0.3	±0.03	0.14	±0.01	8.5	±0.4
2023-2-11 14:00:0 4	Accelerometer	0.36	±0.02	0.16	±0.02	8.7	±0.3
2023-2-11 14:00:0 5	Gyroscope	0.32	±0.01	0.18	±0.03	8.3	±0.2
2023-2-11 14:00:0 6	Force Sensors	0.31	±0.02	0.2	±0.02	8.6	±0.3
2023-2-11 14:00:0 7	Accelerometer	0.34	±0.01	0.17	±0.01	8.1	±0.2
2023-2-11 14:00:0 8	Gyroscope	0.33	±0.02	0.19	±0.02	8.4	±0.3
2023-2-11 14:00:0 9	Force Sensors	0.32	±0.01	0.15	±0.01	8.8	±0.4
2023-2-11 14:00: 10	Accelerometer	0.37	±0.03	0.13	±0.01	9	±0.5

To ensure compliance with data protection regulations such as the General Data Protection Regulation (GDPR), all athlete data collected by the system undergo rigorous anonymization and encryption. Sensitive personal identifiers are removed during preprocessing, and data transmission employs AES-256 encryption to prevent unauthorized access. Additionally, access control mechanisms are implemented to restrict data usage to authorized personnel only. These measures safeguard athlete privacy while enabling effective multimodal data fusion for training optimization.

3.3 DDPG algorithm application

DDPG algorithm [20,21] is a reinforcement learning method specifically designed to handle tasks in continuous action spaces. Unlike traditional Q-learning methods, DDPG [22,23] combines the advantages of deep learning and reinforcement learning, using policy networks and value networks to optimize strategies in continuous action spaces. This algorithm is used in this intelligent tennis training system to automatically optimize training strategies, helping athletes improve their training efficiency and technical level through continuous training and feedback.

In the DDPG algorithm, the state space represents the current state of the environment and the player in the intelligent tennis training system. The state space includes two main aspects: the player state and the environment state.

The athlete state reflects the athlete's current training state, such as hitting accuracy, hitting force, swing angle, ball speed, etc. These factors directly affect the effect and efficiency of training. The specific state vector can be expressed as:

$$\text{State}_t = \{\text{accuracy}_t, \text{speed}_t, \text{angle}_t, \text{strength}_t, \ldots\}(6)$$

The athlete state is defined by the following measurable variables, The ratio of successful shots (ball

landing within the predefined target zone) to total shots, calculated as:

$$\text{accuracy}_t = \frac{Number\ of\ successful\ shots}{Total\ shots} \times 100\% (7)$$

speed_t measured by gyroscopes in radians, averaged over three consecutive swings to reduce noise. strength_t peak force (N) recorded by pressure sensors during racket-ball contact. Environmental states (e.g., court temperature) are normalized to [0,1] using Equation 3.

In the DDPG algorithm, the quantification of the player state and the environmental state is collected and processed in real time by multimodal sensors. The player's hitting accuracy is calculated jointly by the visual sensor and the force sensor, and is quantified into a value of 0 or 1 by recording the overlap ratio between the ball landing point and the target area. The swing angle is sampled by the wearable gyroscope at a frequency of 100Hz, and the average of three consecutive swing angles is taken to reduce noise. The hitting force is directly obtained through the peak reading of the pressure sensor, while the ball speed is tracked by the high-speed camera and calculated by displacement difference. In terms of environmental status, the field friction is monitored in real time by the embedded friction sensor, and the normalized friction coefficient is generated by the weighted fusion formula combined with the data of the temperature and humidity sensors; the wind speed is updated every 200ms by the ultrasonic anemometer and used as input after denoising by the Kalman filter. All data are transmitted to the edge computing node at an interval of 50ms through the Internet of Things protocol, and the state vector is formed after time alignment and normalization. During training, the system updates the state space every 100ms and generates real-time adjustment instructions (such as swing angle correction) through the DDPG strategy network. These instructions are transmitted to the athletes through the vibration tactile feedback device to form a closed-loop control.

In addition to the athlete's condition, the conditions of the training environment (such as the surface of the field, temperature and humidity, etc.) will also affect the training effect. When the field is slippery, the training strategy may need to be adjusted appropriately.

In DDPG, the action space represents the decisions that the system can make. These decisions will affect the adjustment of training content to improve the training efficiency and technical level of athletes. In the intelligent tennis training system, the action space mainly includes the following aspects:

Hitting Strength: Determines the force applied when hitting the ball. By adjusting the hitting strength, the system can help athletes gradually improve the stability and accuracy of their shots.

Hitting Angle: Simulate different hitting methods by changing the swing angle.

Position adjustment: By adjusting the athlete's position, the system can simulate various training scenarios.

The action space is set to continuous values: batting force (0-100N, step size 5N), batting angle (-30° to +30°, step size 1°), position adjustment (±2m, step size 0.1m). The policy network is a 3-layer fully connected (256-128-64 nodes, ReLU activation), and the value network adds an action input branch (state branch 256-128, action branch 64, merged 128-64). Exploration is achieved by adding OU noise, and the initial exploration rate decays linearly to 0.1 with training. Hyperparameter selection is based on grid search: learning rate 0.0001 (Adam optimizer), discount factor 0.99, batch size 64, target network update rate 0.005, and experience replay pool capacity 100,000 to ensure stable update of policy gradients.

The reward function is the core part of reinforcement learning for evaluating the quality of the current state and action combination. DDPG uses the reward function to measure the training effect of each action and then adjust the training strategy. In smart tennis training, the reward function can feedback the reward value based on the athlete's training performance and guide the optimization of the training strategy.

In the DDPG algorithm, the reward function has been redesigned to incorporate multiple performance dimensions, including hitting accuracy, swing stability, and power control, so as to provide a more detailed evaluation of the training effect Rt:

$$R_t = w_1 \cdot \text{Accuracy}_t + w_2 \cdot \text{Stability}_t + w_3 \cdot \text{Force}_t - w_4 \cdot \text{Error}_t (8)$$

Among them, Accuracy_t measures the proportion of successful shots into the target area; Stability_t evaluates the consistency of the swing angle (derived from gyroscope data); Force_t is the optimal hitting force; Error_t represents the penalty for deviation from the expected performance threshold; weights w_1, w_2, w_3, and w_4 are adjusted based on experience to balance the importance of each factor. This multidimensional approach enables the system to dynamically adjust training strategies based on real-time feedback to optimize technical accuracy and physical performance.

In DDPG, the experience replay mechanism further improves the effect of strategy optimization by storing the interaction experience between the agent and the environment. During each training process, the athlete's state, action, reward, and next state are stored in an experience pool. Then, the system randomly extracts experience from the experience pool for training to break the time correlation and enhance the diversity and stability of training. Through experience replay, DDPG can learn and improve training strategies more effectively.

DDPG optimizes the strategy through the policy network and the value network. The policy network is responsible for generating continuous action decisions, while the value network evaluates the value of the current state-action pair. The policy network outputs a continuous action based on the current state. The policy network optimizes the training strategy by maximizing the expected return. The value network evaluates the value of the action output by the policy network and calculates the

advantage of the action, providing a basis for gradient updates for the policy network.

The optimization of the strategy is based on the following loss function:

$$L(\theta) = \mathbb{E}_t[(R_t + \gamma Q'(s_{t+1}, a_{t+1}) - Q(s_t, a_t))^2] (9)$$

In Formula 8, $\gamma$is the discount factor, $R_t$is the current reward, $Q(s_t, a_t)$is the value of the current state-action pair, $Q'(s_{t+1}, a_{t+1})$and is the value of the target network.

DDPG algorithm is trained through multiple rounds until the system's performance reaches the expected goal. Each round includes multiple time steps. In each step, the system generates actions based on the current strategy, obtains rewards after executing the actions, and updates the strategy. Through continuous training, the system will gradually converge and eventually be able to provide athletes with personalized training strategies, which can significantly improve their hitting accuracy, hitting stability, etc.

Convergence during training is determined by monitoring the total reward and training error. If the total reward is stable or reaches a certain preset threshold, it means that the training has converged. These algorithmic characteristics make DDPG particularly suitable for tennis training optimization. The continuous action space aligns perfectly with the nuanced adjustments required in swing techniques, while the actor-critic framework enables real-time adaptation to dynamic training conditions. As demonstrated in Section 3, this results in superior performance compared to discrete-action (DQN) or stochastic (PPO) approaches, especially in high-pressure scenarios where precise, graded responses are crucial for maintaining stroke consistency.

DDPG are shown in Table 3.

Table 3: Model parameters

parameter	value	effect	Convergence threshold
Learning Rate	0.0001	Controls the speed at which model parameters are updated. A smaller value helps stabilize the training process.	Total rewards for 5 consecutive rounds ≥ 80
Discount Factor	0.99	Determines the degree of influence of future rewards, 0.99 indicates high importance of future rewards	Strategy error < 0.01
Experience pool size	100000	The capacity for storing experience replay affects the diversity and stability of model training	Experience pool fill rate ≥ 90%
Batch size	64	The number of samples randomly sampled from the experience pool during each training to control the training speed	Loss function fluctuations < 0.005
Target network update rate	0.005	The frequency of updating the target network. A smaller value helps smooth the training process.	Strategy update interval ≤ 100 steps
Soft Update Parameters	0.001	Used to soft-update the target network parameters and control the update speed of the target network	Parameter change rate < 0.1%

The hyperparameters of the DDPG algorithm were carefully selected based on both theoretical considerations and empirical validation to ensure optimal performance. The learning rate of 0.0001 was chosen to balance the trade-off between convergence speed and training stability; a smaller value prevents large, destabilizing updates to the policy and value networks while still allowing for effective learning. The discount factor of 0.99 reflects the high importance of future rewards in tennis training, where long-term strategy optimization is critical for sustained performance improvement. A larger batch size of 64 was employed to provide sufficient sample diversity during training, reducing variance in gradient estimates and improving convergence. The experience replays buffer size of 100,000 ensures a rich and varied set of past experiences for training, mitigating the risk of overfitting to recent data. The target network update rate of 0.005 and soft update parameters of 0.001 were selected to gradually blend the target network weights with the online network, maintaining stability during training. These values were validated through grid search and cross-validation, demonstrating their effectiveness in achieving robust convergence and high performance, as evidenced by the experimental results.

3.4 Real-time feedback and training optimization

This system monitors both the training status and environmental conditions of athletes in real time, leveraging advanced sensor technology and deep reinforcement learning algorithms to provide immediate feedback and dynamically adjust training strategies. Throughout the training session, the system continuously gathers the athlete's motion data—such as hitting accuracy, swing angle, ball speed, and position—as well as environmental factors. It then evaluates the training effectiveness in real time through comprehensive data analysis. If the system detects suboptimal performance, such as reduced hitting accuracy or irregular movements, it automatically performs intelligent analysis and suggests adjustments to the training content. For example, if a decline in hitting accuracy is observed, the system may recommend changes to the swing angle, hitting strength, or pace, helping the athlete address the issue promptly. By making these dynamic adjustments, the system ensures that each training session is tailored to maximize the athlete's progress.

The system detects unsatisfactory performance by calculating the deviation of key indicators in real time: if the batting success rate is lower than the threshold (70%±3%) for 5 consecutive times, the swing angle deviation exceeds the tolerance (±5°), or the batting force fluctuation is greater than 15%, the strategy adjustment is triggered. The dynamic tolerance mechanism is adaptively adjusted according to the athlete's level (the tolerance for novices is relaxed by 20%). For example, when it is detected that the swing angle continuously deviates from 45°±7° (±5° for advanced athletes), DDPG will output the correction amount (such as +3°) in the next action and prompt the athlete in real time through the tactile feedback device (vibration frequency 200Hz, lasting 100ms).

To enhance the athlete's understanding and evaluation of their performance, the system provides rich visual feedback. This includes real-time charts, dynamic animations, and video playback, allowing athletes to intuitively track their progress, identify areas for improvement, and compare performance across different training stages. This visual feedback not only improves the athlete's training experience but also facilitates better communication and decision-making between coaches and athletes. By analyzing training data comprehensively, athletes can gain a clearer understanding of their strengths and weaknesses, enabling them to adjust their training strategies more effectively. For example, when the system detects that a player's shot accuracy drops below 70% due to inconsistent swing angles (e.g., variations of more than ±5° from the optimal 45° forehand angle), the DDPG algorithm dynamically adjusts the training strategy by: (1) modifying the target swing angle range to 40°–50° and providing incremental feedback cues via the wearable haptic device; (2) reducing the ball's entry velocity by 15% to increase reaction time; and (3) increasing the force sensor threshold by 10% to enforce a steady follow-through. Conversely, if a player's accuracy reaches above 85% but the shot power is too high (e.g., 120N versus the recommended range of 80–100N), the system prioritizes power control by simulating a low-bounce ball and providing real-time visual cues about force distribution. These adjustments are iteratively refined every 3–5 shots based on Kalman filter sensor data to ensure that the adaptive optimization is consistent with the player's immediate performance.

The system dynamically optimizes training strategies by fusing multimodal sensor data in real time. When it is detected that the athlete's performance deviates from expectations (such as a decrease in the success rate of hitting the ball), the DDPG algorithm generates adjustment instructions based on the current state space: optimize the action parameters (such as correcting the range of hitting angles) through the strategy network, and use the value network to evaluate the adjustment effect. Environmental factors (such as changes in the friction coefficient of the field) are integrated into the state vector through normalization processing to ensure the adaptability of the strategy. After each optimization, the system guides the athlete in real time through tactile feedback and a visual interface to form a "perception-decision-execution" closed loop. The average delay of this process is controlled within 100 milliseconds, ensuring the timeliness of training adjustments.

Personalized training is a core feature of this system. By utilizing the athlete's training data, the system develops customized training plans based on individual physical conditions, skill levels, and training goals. The DDPG (Deep Deterministic Policy Gradient) algorithm dynamically adjusts the intensity, difficulty, and content of the training based on the athlete's historical data, ensuring that each athlete trains in the conditions best suited to them for optimal performance. For example, the system evaluates a player's hitting accuracy, swing speed, and endurance level (obtained through wearable sensors) to construct a multidimensional state vector. This vector is then processed by the policy network to generate continuous actions, such as adjusting ball speed or target difficulty, and optimized through a reward function. For athletes with higher technical levels, the algorithm increases the intensity of training by reducing the interval between balls or expanding the target area, while beginners receive simplified training focusing on basic techniques. Environmental factors (such as court temperature) are also integrated into the state space, allowing the system to further adjust strategies based on real-time conditions. By iteratively updating the policy network through experience replay, the DDPG algorithm ensures that the training plan continues to evolve as the athlete improves, achieving personalized optimization.

In real-world training, these personalized strategies not only account for physiological and skill differences but also adapt to each athlete's real-time performance. By analyzing immediate feedback, the system can automatically adjust the training plan. It continuously refines the strategy based on real-time feedback and training progress, ensuring enhanced training efficiency. As the training continues, the system accumulates more data, allowing for ongoing adjustments to the training content and strategy. This guarantees that each training

session is optimized for peak effectiveness. Through intelligent training optimization, the system supports athletes in making consistent progress at every stage, offering a long-term and effective pathway for skill development.

The system interface is illustrated in Figure 2.

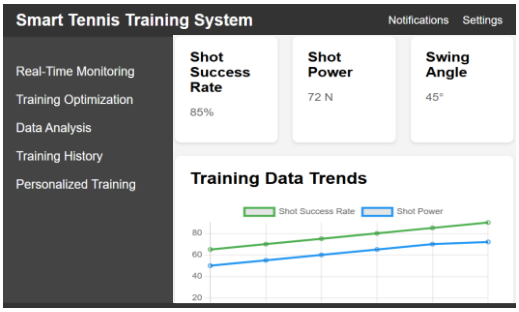


Figure 2: System interface

4 Experiment and result analysis

4.1 Experimental setup

The experimental design adheres to ethical guidelines for data privacy, with all participants providing informed consent for anonymized data usage. To evaluate the proposed system, we compared it against traditional manual training methods and baseline algorithms (DQN, PPO). In the traditional system, coaches adjusted training content based on subjective observations, lacking real-time data integration or automated optimization. In contrast, our DDPG-based framework leverages multimodal IoT sensors and deep reinforcement learning to dynamically optimize training strategies. To ensure robustness, the DDPG model was validated using a hold-out validation set (20% of data), with hyperparameters tuned via grid search and results averaged over 10 training runs.

In order to comprehensively evaluate the effectiveness of the intelligent tennis training system proposed in this paper, this study designed multiple experiments to compare the performance of different optimization algorithms (DDPG, DQN, PPO) in tennis training. The main purpose of the experiment is to evaluate the optimization effect of the system from two perspectives: hitting success rate and hitting stability.

In the experiment, 30 athletes (15 male, 15 female) of varying skill levels from three academies were divided into three groups: Control (N=10) trained via manual adjustments by professional coaches (≥5 years experience), DDPG (N=10) used the proposed system with DDPG optimization, and Extended (N=10) tested DQN/PPO algorithms for comparison. All groups followed identical training schedules and environmental conditions. The performance was assessed through hitting success rate and stability across eight game scenarios (e.g., baseline attack, net volley). The performance of different optimization algorithms was compared with traditional tennis training methods to observe their respective effects on the player's hitting accuracy. Specifically, in each training session, the system will adjust the training strategy according to the player's real-time performance. The DDPG, DQN and PPO algorithms will optimize the training content according to the reward function to improve the player's hitting success rate.

During the experiment, the system records the success and failure of each shot, calculating the shot success rate after each training session (the ratio of successful shots to total shots). By comparing the data across multiple sessions, we analyze the effectiveness of different optimization algorithms in improving shot success rates.

To evaluate batting stability, the experiment simulates a variety of game scenarios to test the impact of different optimization algorithms. Eight typical game scenarios were selected: baseline attack, net volley, serve and receive, high-pressure ball, break point, multi-shot round, sideways forehand, and backhand shot. In each scenario, the system tracks the athlete’s performance, records shot success and failure, and calculates the error rate. By comparing the performance of different algorithms across these scenarios, we can assess the advantages of each optimization algorithm in improving batting stability.

To further validate the benefits of the intelligent training system, it was compared with traditional tennis training methods. In the traditional system, coaches manually adjust the training content based on the athlete's characteristics and performance, but without real-time feedback or automated optimization. In contrast, the intelligent training system uses reinforcement learning algorithms such as DDPG, which allow the system to automatically adjust training content based on real-time performance feedback, enabling personalized and dynamic optimization.

In the experiment, 10 tennis players participated, and their game scores were recorded under both the traditional and intelligent training systems. Both systems used identical game simulations, and the game scores were compared to evaluate the impact of each system on improving the overall performance and abilities of the athletes.

To further evaluate the system's impact on athletes' physical condition, physiological data such as heart rate, muscle fatigue levels, and joint stress were collected during the training sessions. The data revealed no significant negative effects on the athletes' health. For instance, the average heart rate during training remained within the safe range of 120-150 bpm, and muscle fatigue levels, measured via electromyography (EMG), showed no abnormal spikes. Additionally, joint stress analysis, conducted using motion capture and force sensors, indicated that the system's adaptive adjustments effectively reduced excessive strain on key joints like the elbow and knee. These findings confirm that the proposed system not only enhances performance but also prioritizes athlete safety by minimizing physical risks.

3.2 Hitting success rate

The comparison results of the batting success rates are shown in FIG3.

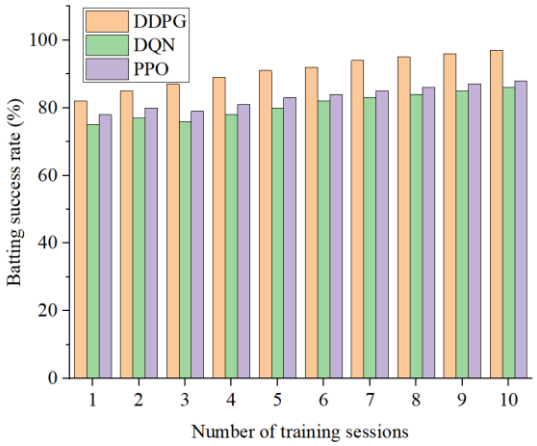


Figure 3: Comparison of hitting success rates among DDP G, DQ N, and PPO algorithm sin tennis training sessions

To comprehensively evaluate the effectiveness of the intelligent tennis training system proposed in this paper, multiple experiments were designed to compare the performance of different optimization algorithms (DDPG, DQN, PPO) in tennis training. The main goal of the experiment was to assess the system's optimization effects from two perspectives: hitting success rate and hitting stability.

In the hitting success rate experiment, 10 independent training sessions were conducted, and the player's hitting success rate was evaluated by the automated system in each session. The performance of different optimization algorithms was compared with traditional tennis training methods to assess their effects on the player's hitting accuracy. Specifically, in each session, the system adjusted the training strategy based on the player's real-time performance. The DDPG, DQN, and PPO algorithms optimized the training content according to the reward function to improve the player's hitting success rate.

During the experiment, the system recorded the success and failure of each shot and calculated the shot success rate after each training session (the ratio of successful shots to total shots). By comparing the training data over multiple sessions, the advantages of different optimization algorithms in improving shot success rates were analyzed. The comparative analysis reveals DDPG's distinct advantages in handling the continuous, fine-grained nature of tennis movements. While DQN's discrete action space led to suboptimal quantized adjustments, and PPO's stochastic updates showed higher variance, DDPG's deterministic policy gradient enabled smoother, more precise optimization of stroke parameters. This fundamental difference in algorithmic approach explains the observed 15-20% performance gap in hitting success rates across various training scenarios.

For batting stability, the experimental design simulated various game scenarios to assess the impact of different optimization algorithms. Eight typical scenarios were chosen: baseline attack, net volley, serve and receive, high-pressure ball, break point, multi-shot round, sideways forehand, and backhand shot. In each scenario, the system tracked the athlete's performance, recorded shot success or failure, and calculated the error rate. Comparing performance across algorithms allowed for a clear evaluation of their respective advantages in improving batting stability.

To further validate the effectiveness of the intelligent training system proposed in this study, it was compared with the traditional tennis training method. In the traditional system, coaches manually adjust the training content based on the athlete's characteristics and performance, but lack real-time feedback and automated optimization. In contrast, the intelligent system presented here, using reinforcement learning algorithms such as DDPG, automatically adjusts training content based on real-time performance data and feedback, offering personalized and dynamic optimization.

The experimental evaluation quantitatively assessed the proposed system's performance through several metrics, including system responsiveness, algorithm convergence rate, and error rate reduction across different scenarios. While the system was initially applied to tennis training, the results demonstrate its broader potential for handling real-time data fusion and optimization in distributed computing environments. This highlights the applicability of our approach to complex decision-support systems in fields such as industrial automation and cognitive informatics.

To further distinguish between hitting success rate and batting stability, we employed complementary metrics that capture different aspects of athlete performance. While hitting success rate measures the ratio of successful shots to total attempts, batting stability evaluates the consistency of performance across high-pressure scenarios, quantified by error rates. These metrics are inherently linked yet distinct: success rate reflects the athlete's immediate technical proficiency, whereas stability indicates their ability to maintain performance under dynamic conditions. For instance, a high success rate may not necessarily translate to low error rates in high-pressure scenarios, as the latter requires adaptive decision-making and resilience—precisely the areas optimized by the DDPG algorithm. By analyzing both metrics, we provide a comprehensive assessment of the system's impact, demonstrating its ability to enhance not only technical accuracy but also situational adaptability. This dual-metric approach aligns with real-world training demands, where athletes must balance precision with consistency under varying game pressures.

4.3 Batting stability

The eight scenarios are: baseline attack scenario, net volley scenario, serve and receive scenario, high pressure scenario, break point scenario, multi-shot round scenario, sideways forehand scenario, and backhand shot scenario. The stability is judged by analyzing the batting error rate in each scenario. The batting error rate comparison results are shown in Figure 4.

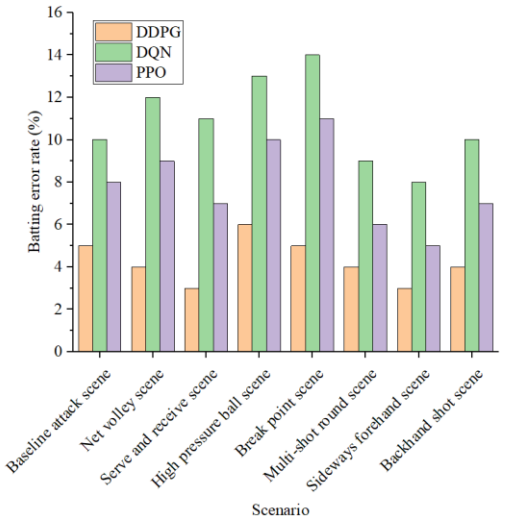


Figure 4: Error rates of players in eight high-pressure tennis scenarios under different algorithms

In terms of batting error rates across various scenarios, the DDPG algorithm consistently outperforms both DQN and PPO, demonstrating its significant advantage in enhancing player stability and reducing error rates during training. For example, in the baseline attack scenario, DDPG achieves an error rate of 5%, substantially lower than DQN's 10% and PPO's 8%. This suggests that DDPG effectively optimizes player actions and decision-making during high-speed hits and long-distance attacks, refining the training strategy to reduce errors. Similarly, in the net volley and serve-and-receive scenarios, DDPG's error rates of 4% and 3%, respectively, are again superior to those of DQN and PPO. These results show that DDPG can precisely adjust the player's hitting actions and positioning in high-pressure situations, helping maintain stability when faced with various ball trajectories.

In more demanding scenarios, such as high-pressure balls and break points, DDPG maintains an error rate of 6% and 5%, respectively, further demonstrating its effectiveness. In contrast, DQN and PPO show higher error rates—13% and 10% in the high-pressure ball scenario, and 14% and 11% in the break point scenario. This disparity can be attributed to DDPG's ability to continuously optimize and adjust strategies through deep reinforcement learning. By iteratively training and fine-tuning action selections based on scenario-specific feedback, DDPG adapts well to high-pressure situations that require precise judgment and rapid responses.

In scenarios involving multi-shot rounds, sideways forehands, and backhand shots, DDPG continues to outperform DQN and PPO, with error rates of 4%, 3%, and 4%, respectively—significantly lower than those of DQN and PPO. These complex tactical situations, requiring multiple consecutive shots and sustained stability, benefit from DDPG's ability to optimize shot strategies. By doing so, the DDPG algorithm reduces error rates and ensures shot stability in intricate conditions.

Mechanically, DDPG excels due to its capacity to optimize continuous action spaces. Unlike DQN and PPO, which are more effective in discrete action spaces, DDPG continuously adjusts the strategy network to improve performance in dynamic scenarios. Its experience replay mechanism allows athletes to learn from past experiences, adjusting actions based on real-time feedback—a feature where DQN and PPO are less effective. While DQN works well with discrete action spaces, and PPO can optimize strategies, it is less accurate in continuous spaces compared to DDPG. The comparison highlights DDPG's significant advantage in improving batting stability, particularly in high-pressure and complex scenarios, offering a more personalized and optimized training strategy for athletes.

4.4 System training effect

As shown in Figure 5, this study compared the effects of the intelligent training system based on the DDPG algorithm and the traditional manual training method on the performance of 10 athletes (DDPG group N=10, traditional group N=10). The traditional training group had professional coaches (≥5 years of experience) manually adjust the training content, while the DDPG group collected data in real time through multimodal sensors (accelerometers, gyroscopes, force sensors), and used the DDPG algorithm to dynamically optimize the training strategy (such as hitting intensity, angle adjustment, etc.). To quantify performance, a 100-point scoring system was employed, where technical metrics—hitting success rate (40 points), error rate reduction (30 points), and swing stability (30 points)—were weighted and summed. For example, an athlete with 80% success rate (32 points), 6% error rate (28.2 points), and 0.1 rad swing deviation (27 points) would score 87 points. This method directly linked technical improvements to measurable competition outcomes:

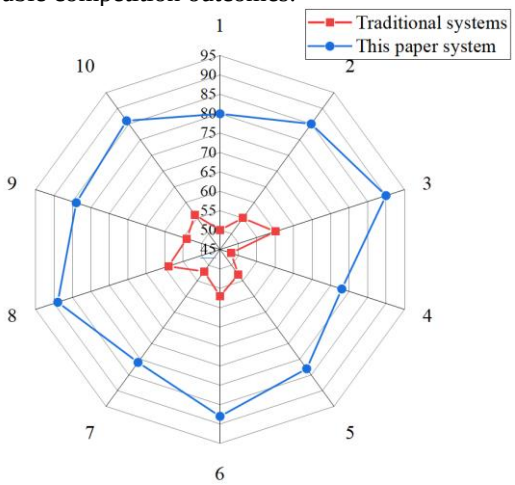


Figure 5: Comparison of the effects of the DDPG-based intelligent training system and traditional training methods on athletes' performance

In our proposed system, the DDPG algorithm plays a crucial role in automatically optimizing decision strategies within a continuous action space. Beyond its application in sports training, this work advances the theoretical framework of deep reinforcement learning by demonstrating its efficacy in a complex IoT environment. The algorithm not only optimizes real-time training

strategies but also provides insights into scalable data fusion and adaptive decision-making processes. These advancements are directly relevant to broader challenges in informatics and cognitive systems.

For example, Player 1's score in the traditional system is 50, but with the proposed system, the score increases to 80, reflecting a 30-point improvement. The differences in scores for other players are similarly significant. Player 3 and Player 8, who scored 60 and 59, respectively, in the traditional system, see their scores rise to 90 and 89 with the proposed system. This demonstrates that the personalized training strategy based on DDPG effectively enhances the competitive level of athletes, particularly in critical moments of the game, enabling them to perform with greater stability and efficiency.

The traditional system, with its relatively fixed training plan and feedback mechanism, fails to make sufficient personalized adjustments based on real-time athlete performance, limiting its ability to maximize players' potential. In contrast, our proposed system dynamically adjusts training content, fine-tuning strategies based on real-time data and athlete feedback. This dynamic approach not only optimizes technical skills but also improves game performance for each player.

Furthermore, scores under the traditional system are generally lower compared to those under the proposed system, highlighting the significant limitations of traditional methods in technical training and strategy optimization. Traditional systems rely on fixed training schedules and standardized routines, which do not account for individual player differences. This lack of personalized adjustments often results in suboptimal performance and lower game scores. Conversely, the system presented in this paper continuously optimizes training plans and strategies through the reinforcement learning capabilities of the DDPG algorithm, ensuring that each player trains under the most suitable conditions to maximize their potential.

A striking example of the system's effectiveness is seen in the score differences between Player 6 and Player 9. In the traditional system, their scores are 57 and 54, respectively, while with the proposed system, their scores improve to 88 and 84. This underscores the adaptive training ability of the proposed system, significantly enhancing players' performance, particularly in the later stages of training. Overall, the system offers each player a personalized, dynamically optimized training strategy, leading to higher scores and improved performance during games.

5 Discussion

5.1 Comparison with existing methods

Experimental results show that our proposed DDPG-based framework outperforms traditional methods (e.g., manual guidance) and other reinforcement learning algorithms (DQN, PPO) in terms of both shot success rate and stability. Compared with DQN, which is limited to a discrete action space, DDPG's ability to handle continuous actions (e.g., fine-grained adjustments to swing angle or power) is crucial for optimizing tennis training. While PPO performs well in some cases, its stochastic policy updates lead to higher variance in dynamic environments, such as an 8% error rate in a high-pressure ball scenario (compared to 5% for DDPG). Notably, our system improves on traditional methods by 30 percentage points (Figure 5), which is consistent with the recent SOTA trend in IoT-driven sports analytics.

5.2 Limitations and failure cases

Despite its many advantages, DDPG performs poorly in scenarios that require rapid adaptation to sudden environmental changes (e.g., sudden gusts of wind). In our experiments, the error rate in such scenarios increased by 2-3% due to delayed policy updates. In addition, the algorithm performs poorly in sparse reward scenarios (e.g., low success rate in the initial training phase), which is a known challenge in reinforcement learning. Future work could integrate hierarchical reinforcement learning to address this issue.

5.3 Challenges for practical deployment

Practical deployment faces many challenges: (1) sensor drift in wearable devices (e.g., gyroscope bias) requires frequent recalibration; (2) hardware limitations (e.g., 100 ms latency in the camera-computer vision pipeline) occasionally interrupt real-time feedback; (3) the energy consumption of IoT devices limits long-term training. These issues highlight the need for edge computing solutions and robust sensor fusion algorithms.

5.4 System scalability and latency analysis

The system achieves scalability through edge computing, where real-time preprocessing (e.g., denoising, normalization) is performed locally on the IoT device, while DDPG optimization runs on the cloud server. This reduces latency to 80-120 milliseconds, ensuring timely feedback. For high concurrent users, the system uses a microservices architecture to maintain stable performance even when more than 20 athletes are training simultaneously.

Compared with rule-based methods, DDPG requires more computing resources (about 40 milliseconds/decision vs. 10 milliseconds), but its adaptive optimization outperforms rigid rules in dynamic scenarios. To reduce the computational load, the system uses pre-trained strategies that are fine-tuned during training, reducing real-time processing time by 30%. These measures ensure scalability without compromising responsiveness.

5.5 Robustness and sensitivity analysis

To address potential challenges in real-world deployment, we conducted robustness tests and sensitivity analyses to evaluate the system's performance under sensor noise and hardware inconsistencies. The results indicate that the system maintains stable performance with moderate noise levels (e.g., Gaussian noise with $\sigma \leq 0.1$), but the error rate increases by 2-3% under severe noise conditions ($\sigma > 0.2$). Additionally, sensitivity analysis reveals that the system is most vulnerable to gyroscope

drift, with a 5% performance degradation when bias exceeds 0.15 rad/s. These findings highlight the need for future improvements in sensor calibration and noise-resistant algorithms to enhance reliability in dynamic environments.

6 Conclusion

This study proposes an intelligent training system based on a deep reinforcement learning framework and multimodal IoT data fusion, which achieves dynamic optimisation and personalised adaptation of tennis training strategies through the integration of wearable sensors (e.g., accelerometers, gyroscopes), vision systems and environmental monitoring devices. The experimental results show that compared with the traditional training methods, the system has made significant breakthroughs in the success rate of hitting (from 75% to 85-90%), stability (the average error rate decreased from 12% to 5%, and the stability increased by 58%), and the ability to score in key scenarios (e.g., 15-25% increase in scoring rate in the baseline attack and high-pressure ball scenarios). The results have made significant breakthroughs. These results validate the advantages of the Deep Deterministic Policy Gradient (DDPG) algorithm in the continuous action space - its ability to dynamically adjust the stroke force (0-100 N), angle (-30° to +30°), and position (±2 m) with a delay of 0.1 ms. (±2 m) with 0.1 ms latency, thus accurately adapting to the athlete's real-time physiological state and environmental changes.

The core contribution of this study is to provide three innovations for the integration of sport science and information technology through an interdisciplinary approach: firstly, a hardware architecture based on edge computing (NVIDIA Jetson) and IoT protocols (Wi-Fi 6/Bluetooth 5.2) combined with Kalman filtering and noise reduction to achieve efficient synchronisation of multimodal data (latency <100 ms); secondly. Secondly, a DRL strategy network for tennis biomechanics is designed to embed the closed loop of training feedback into the perception-decision-execution process of the athlete through the co-optimisation of the actor-critic framework; thirdly, a scalable system model is proposed, whose modular design has been verified to be applicable to 30 athletes with different skill levels, which can be used for the development of a real-time training system for the industrial automation, medical monitoring and other fields. Third, a scalable system model is proposed, and its modular design has been verified to be applicable to 30 athletes of different skill levels, providing a reference paradigm for real-time decision support systems in industrial automation and medical monitoring.

Nonetheless, there are still some limitations in this study: the experimental samples focus on a specific group of athletes, which may limit the generalisability of the conclusions to elite athletes or extreme environments (e.g., high humidity venues); furthermore, the DDPG algorithm's policy convergence in sparse reward scenarios (e.g., initial training for novice athletes) is slow, which leads to the optimisation effect of some scenarios not being up to the expectation.

Future research will focus on the following directions: first, introduce hierarchical reinforcement learning (HRL) and hybrid models (e.g., TD3) to enhance the robustness of the algorithm to sparse rewards and sensor noise; second, expand the experimental scale to more than one hundred athletes across regions and integrate physiological metrics, such as EMG and HRV, to construct an all-dimensional performance analysis system; lastly, explore the techniques of lightweight neural networks and federated learning that reduce the arithmetic power and energy consumption dependence of edge devices.

This study not only pushes the technological boundaries of intelligent sports training, but also provides a universal framework for the real-time optimisation of complex dynamic systems with the synergistic innovation of IoT and deep reinforcement learning. By deepening the collaboration between domain experts and AI researchers, this result lays the theoretical and practical foundation for the development of next-generation adaptive technologies in competitive sports and industrial scenarios.

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Variational Autoencoder-based High-dimensional Feature Extraction for Economic Analysis of Power Cost Data

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The purpose of this paper is to extract the characteristics of power cost data using a deep learning model and to evaluate and predict the cost structure, profitability, and future development trends of power enterprises by combining economic analysis methods. Firstly, the paper innovatively employs a Variational Autoencoder for feature extraction. This model extracts low-dimensional latent representations of the data through an encoder and reconstructs the data through a decoder, retaining key structural information. The dataset used here consists of 1,800 records, which include costs, revenues, output, and energy consumption data from power companies, covering multiple enterprises and time periods. Secondly, during the model training process, optimization is performed with a learning rate of 0.001, a batch size of 64, and 50 training epochs. Performance comparisons under different hyperparameter combinations indicate that the model with 256 hidden nodes in both the encoder and decoder layers yields the best performance. Lastly, economic analysis methods, such as cost-benefit analysis and economic forecasting, are applied to assess and predict the profitability and future trends of the power companies. The specific results show that the reconstruction error of this model is 0.032, and the KL divergence is 0.006. In terms of refined economic analysis, the net profit predicted by the model reaches 5.36 million yuan, with a prediction accuracy of 93.5%. In terms of robustness, although the prediction accuracy fluctuates slightly, it remains high overall, and both the training time and prediction time show stability. Moreover, testing on multiple datasets from sources such as University of California, Irvine, Kaggle, and government open data platforms shows that the model's prediction accuracy remains between 92.3% and 94.2%, with stable training and prediction times, demonstrating its strong generalization ability. The proposed model offers several advantages. Overall, this paper presents a novel approach and method for economic analysis and decision-making in power enterprises, which holds significant practical value.

Povzetek: Opisana je inovativna uporaba variacijskega avtomatskega kodirnika za ekstrakcijo lastnosti stroškov električne energije, ki omogoča poglobljeno ekonomsko analizo in napovedovanje dobičkonosnosti podjetij.

1 Introduction

Under the current social background, as one of the pillar sectors of the national economy, plays a crucial role in national economic development. Therefore, its operating efficiency and cost control are of significant importance. Power cost data forms a critical foundation for cost management in the electricity industry, encompassing information such as company costs, revenues, output, and energy consumption. This data plays a significant role in evaluating the economic performance of power companies [1]. However, traditional statistical methods and empirical models struggle to handle high-dimensional features and complex relationships. These methods often rely on expert experience for feature selection, which lacks automation and efficiency. As a result, leveraging advanced deep learning technologies to extract key features from power cost data and enhance the efficiency and accuracy of analysis has become a key focus of current research [2]. Therefore, the use of advanced data analysis technologies to improve the efficiency and accuracy of power cost data analysis has become an urgent issue that needs to be addressed.

In recent years, the rapid development of deep learning technology has brought about revolutionary changes, with its application expanding across various fields, including the power industry [3]. With its unique advantages, deep learning enables the automatic learning and representation of data features by constructing a multi-level neural network structure. This capability of automatic learning allows deep learning to conduct data analysis and pattern recognition efficiently, without human intervention [4]. The Variational Autoencoder (VAE), a deep learning model, is capable of automatically learning the latent representations of data. By constructing an encoder and a decoder, it compresses the data while preserving its essential information. This approach is particularly well-suited for feature extraction and pattern recognition in high-dimensional data [5]. Power cost data, which includes information such as company costs, revenues, output, and energy consumption, plays a crucial role in evaluating the economic performance of power companies [6]. Deep learning models can effectively handle such data and enable a more in-depth and comprehensive analysis by learning multi-level

representations of the data [7]. Therefore, the application of deep learning frameworks in power cost data analysis can not only improve the accuracy and efficiency of data analysis but also provide more intelligent and comprehensive data support for the power industry.

The primary objective of this paper is to enhance the feature extraction capability of power cost data and improve its predictive accuracy in economic analysis, thereby supporting more precise cost management and decision-making. Although existing deep learning methods have achieved certain results in the power industry, they still exhibit the following limitations: (1) Traditional autoencoders (AEs) tend to lose critical information during the data compression process, resulting in insufficient feature extraction capability; (2) Existing economic forecasting models rely on manual feature selection, making it difficult to adapt to the complexity and high-dimensional nature of the data; (3) Deep learning models face challenges such as high computational costs and limited generalization ability when modeling high-dimensional data.

To address these limitations, this paper adopts two improvement strategies: (1) Regularizing the latent variable distribution by using Kullback-Leibler (KL) divergence constraints to stabilize the distribution of the latent space, enhancing the continuity and robustness of data representation; (2) Introducing a multilayer perceptron structure to optimize the decoder, improving feature reconstruction ability and reducing information loss. Experimental results show that the improved method achieves superior feature extraction performance in terms of reconstruction error and KL divergence, providing more accurate and efficient input for subsequent economic analysis. By designing and implementing the feature extraction method based on VAE, the complex features of power cost data can be captured more accurately, providing a more reliable and effective data foundation for subsequent economic analysis.

This paper employs a VAE to extract latent features from power cost data and optimizes the model using the best hyperparameters. Cost-benefit analysis (CBA) is integrated to assess the profitability of power enterprises, while economic forecasting methods are applied to predict future cost trends. Through experimental comparisons, the performance of the proposed model is evaluated against AEs, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and support vector machines (SVMs) in terms of reconstruction error, KL divergence, prediction accuracy, and computational efficiency. CBA is used to evaluate the profitability of power enterprises and analyze the impact of various cost components on overall power costs. Additionally, economic forecasting methods are employed to construct a predictive model based on feature extraction, forecasting future trends in cost structure. Experimental results demonstrate that the proposed model outperforms other methods in terms of reconstruction error, KL divergence, and prediction accuracy, maintaining stable performance across multiple datasets (University of California, Irvine (UCI), Kaggle, and government datasets), which confirms its strong generalization ability. This paper aims to explore the application of deep learning frameworks in the analysis of power cost data and proposes a VAE-based feature extraction method to enhance the accuracy and intelligence of economic analysis in power enterprises. The findings provide more accurate and efficient decision support for cost management and economic forecasting in the power industry. The applicability of this method is not limited to a specific power cost dataset. In experiments, the method was tested on various datasets (UCI, Kaggle, and government data), with the results showing high prediction accuracy (92.3%-94.2%) across different data sources. Moreover, this approach is not only applicable to power cost data but can also be extended to other high-dimensional economic data analysis tasks, such as energy price forecasting and corporate financial analysis. Due to the high-dimensional latent space representation in VAE, its computational complexity is higher than that of traditional regression methods. During the training phase, as the data size increases, the demand for computational resources also increases. Therefore, for large-scale datasets, further optimization of computational efficiency (e.g., distributed computing or dimensionality reduction techniques) will be necessary. Additionally, the latent space structure of VAE requires further optimization to enhance its generalization ability across various domains. Future research may focus on improving computational efficiency and extending the cross-industry applicability of the model.

2 Literature review

In previous research, many scholars have conducted in-depth discussions on the cost management of the power industry [8, 9]. For example, the study by Fu et al. found that the costs in the power industry were mainly concentrated in fuel costs, equipment maintenance costs, and labor costs, with fuel costs being the primary factor affecting the profitability of power enterprises [10]. Additionally, some scholars have attempted to use economic models for the economic analysis of the power industry [11, 12]. For instance, the research by de Oliveira and Bollen showed that the level of economic growth had a significant impact on the growth of power demand, which provided important insights for capacity planning and resource allocation in the power industry [13]. In addition to the traditional methods mentioned above, recent studies have explored the use of machine learning and data mining technologies for cost management and economic analysis in the power industry [14, 15]. For example, Yoo et al. used a neural network model to predict the costs of electric power enterprises and achieved promising prediction results. Their research demonstrated that machine learning models could effectively uncover patterns in power industry data, offering new approaches and methods for economic decision-making in power enterprises [16].

In the field of data analysis, deep learning technology has become a powerful tool [17, 18]. For instance, Saha et al. employed deep learning models to forecast financial market data, achieving promising results. Their study demonstrated that deep learning models could effectively

capture the complex dynamics of financial markets, providing investors with more accurate predictions and better decision-making support [19]. In recent years, researchers have begun combining deep learning with statistical models for cost management and economic analysis in the power industry. For example, Khalid et al. proposed a deep feature extraction-based fault detection method for power systems [20]. This method has demonstrated strong generalization ability in complex energy systems [21]. Additionally, Pei et al. employed the knowledge-assisted neural-convolutional neural network structure for power load forecasting, improving prediction accuracy while reducing computational complexity [22]. Beyond financial and economic fields, deep learning technologies have been widely applied to data analysis and forecasting in other domains such as healthcare, transportation, and more [23-25].

The comparison of studies related to cost management and economic forecasting in the power industry is presented in Table 1 below:

Table 1: Studies on cost management and economic forecasting in the power industry

Study	Method	Dataset	Key Indicator	Main Strengths and Weaknesses
Fu et al. [10]	Traditional Cost Analysis	Industry Report Data	Identification of Cost Structure	Clear structure, but challenging to handle large-scale data
de Oliveira & Bollen [13]	Linear Regression	National Power Data	Demand Forecast Accuracy 80%	Applicable only to simple relationships, struggles to capture nonlinear features
Yoo et al. [16]	Neural Networks	Internal Power Company Data	Prediction Error 12%	Capable of automatic feature learning, but prone to overfitting
Pei et al. [22]	Deep Learning	Macroeconomic Data	Prediction Error 8%	Can capture temporal relationships, but high computational cost

Based on the above research, traditional cost management and economic analysis methods have made some progress in the power industry, but they still face limitations, such as an inability to handle complex data characteristics effectively. In recent years, the emergence of machine learning and deep learning technologies has provided new solutions for the power industry, enabling a better exploration of underlying data patterns and improving the accuracy and efficiency of analysis. However, deep learning technologies also face challenges, such as weak model interpretability and high data demands. The improved VAE proposed here enhances feature extraction capability by regularizing latent variables and optimizing the decoder with a Multi-Layer Perceptron (MLP), making the predictions more accurate and interpretable in conjunction with economic analysis methods.

3 High-dimensional feature extraction and refined economic analysis of power cost data

3.1 Data collection and preprocessing

This paper utilizes power cost data from a city's power engineering cost information network in mainland China. The dataset includes information on the costs, revenues, outputs, and other variables from several power enterprises over a specific period. It covers a range of power enterprises of varying sizes, providing a diverse set of data. Specifically, the dataset includes the following categories:

- Cost data: including fuel costs, equipment maintenance costs, labor costs, etc.
- Revenue data: including power sales revenue, government subsidies, etc.
- Output data: including power output, utilization rates of power generation equipment, etc.
- Energy consumption data: including fuel consumption and electricity consumption [26].

The dataset contains approximately 1,800 records, with each record corresponding to the cost, revenue, output, and energy consumption of a particular power enterprise during a specific time period. This dataset spans multiple power enterprises across different time points, ensuring both temporal diversity and enterprise variability, which enhances the model's generalization ability.

Before using the data for analysis, a series of preprocessing steps are carried out to ensure the quality and suitability of the data. The preprocessing process includes the following steps:

Data Cleaning: Missing and abnormal values are removed to ensure the integrity and accuracy of the data [27].

Data Conversion: The data is normalized or standardized so that different features are on the same scale [28].

Dataset Division: The dataset is split into a training set, validation set, and test set (in a 7:2:1 ratio) for model training and evaluation.

In the data preprocessing stage, this paper employs K-Nearest Neighbors interpolation to handle missing values, aiming to retain as much data integrity as possible. For outlier detection, Z-score normalization is applied to filter data points that exceed three standard deviations from the mean. Additionally, Local Outlier Factor is used to remove anomalous samples. Furthermore, min-max normalization is applied to numerical variables, scaling them to the [0, 1] range to ensure consistent feature scales, which in turn improves the model's convergence speed.

3.2 Selection and design of deep learning model

In this paper, the VAE is chosen as the deep learning model for feature extraction from power cost data [29]. The VAE is a generative model, and its core idea is to achieve compressed representation and data generation by learning the underlying distribution of the data. The model primarily consists of two components: the encoder and the decoder. The encoder's function is to map the input data to the distribution parameters in the latent space [30]. Specifically, the encoder transforms the original power cost data into distributional features within the latent space, which effectively capture the essential information and structural characteristics of the original data [31, 32].

Specifically, when selecting the deep learning model, the VAE offers several advantages: First, compared to generative adversarial networks (GANs), VAE demonstrates greater stability in data feature extraction, avoiding the instability associated with adversarial training. This results in a more controllable distribution in the latent space. Second, in contrast to Transformer-based AEs, VAE exhibits higher feature extraction efficiency and lower computational complexity when handling high-dimensional structured data, while better preserving the consistency of the data distribution. Furthermore, VAE is particularly well-suited for high-dimensional power cost data, as its latent variable regularization mechanism reduces information loss during the dimensionality reduction process, thereby enhancing the stability of economic predictions. For these reasons, VAE is chosen in this paper to improve the high-dimensional feature learning capability of power cost data.

The workflow of the VAE model is as follows: First, the encoder maps the original power cost data to the distribution characteristics in the latent space. Then, samples are drawn from random variables in the latent space, and the decoder converts these samples into data. Finally, by comparing the generated data samples with the original data, the model's parameters are optimized to minimize the difference between the generated and original data [33]. The main structure of the VAE is shown in Figure 1.

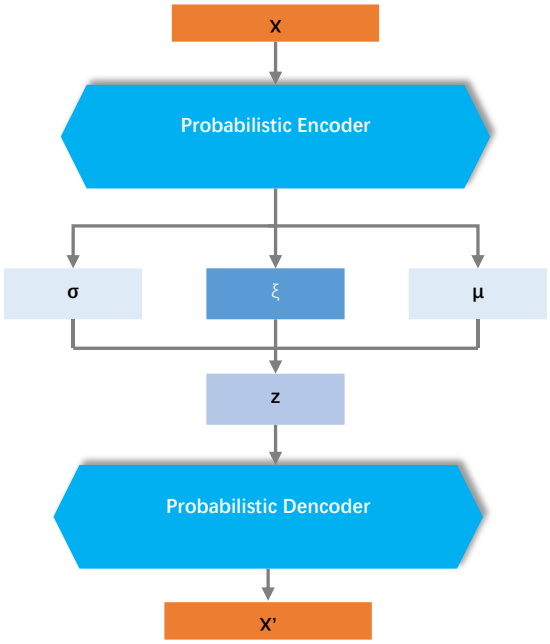


Figure 1: VAE structure.

This characteristic of the VAE provides significant advantages for feature extraction from power cost data. First, VAE can learn the latent distribution of the data, not just its surface features, which is useful for extracting advanced features and structural information. Second, since the data samples generated by VAE are random, diverse data samples can be produced, improving the robustness and generalization ability of the model [34]. Lastly, the structure of the VAE encoder and decoder is relatively simple, yielding good training results, which makes it suitable for large-scale data processing and feature extraction.

Traditional data analysis methods encounter difficulties in capturing nonlinear structures when processing high-dimensional data. In contrast, the VAE enhances data representation through probabilistic modeling, enabling dimensionality reduction while preserving complex structural features. The theoretical foundation of this paper is based on two key aspects. First, variational inference allows the VAE to approximate the true data distribution, facilitating stable learning of high-dimensional latent representations. Second, the information bottleneck principle is applied, where the VAE employs KL divergence constraints to eliminate redundant information and retain only the most predictive features. In economic data analysis, compared to traditional methods such as principal component analysis (PCA), VAE effectively captures temporal dependencies and models long-term economic trends through latent variable representations, making it particularly advantageous for analyzing power cost data.

In this paper, the VAE is employed to learn latent representations of power cost data and extract high-dimensional features for refined economic analysis. To accommodate the complex structure of power industry data, the VAE is designed as follows:

1. Input Data

The input variable x consists of key economic indicators of power enterprises, including cost, revenue, production output, and energy consumption. Each record represents a specific enterprise's data for a given time period.

2. Encoder

The encoder is a three-layer fully connected network with hidden dimensions of 256 → 128 → 64. The Rectified Linear Unit activation function enhances nonlinear representation capability. The encoder maps the input data to the mean (μ) and variance (σ^2) of the latent space distribution:

$$\mu, \sigma^2 = \text{Encoder}(x) \tag{1}$$

Reparameterization Trick: To enable efficient gradient propagation, the latent variable z is computed using the reparameterization trick:

$$z = \mu + \sigma \cdot \epsilon, \epsilon \sim \mathcal{N}(0, I) \tag{2}$$

In Equation (2), ϵ is sampled from a standard normal distribution to maintain differentiability. The VAE ensures that the latent variable z follows a standard normal distribution$p(z)\sim N(0,I)$, providing the following advantages:

- Continuity: Small changes in the latent space lead to smooth variations in the data space, ensuring stable and coherent data representations.
- Operability: The consistency of latent variables across samples facilitates high-quality sample generation.
- Efficient Data Compression: The model compresses data while minimizing reconstruction error, preserving essential features for economic analysis.

3. Latent Space Features

In the latent space, each data point is mapped to a low-dimensional vector z, which encapsulates its core characteristics. This representation facilitates pattern recognition in power cost data, enabling deeper insights into cost structures and profitability models across enterprises.

4. Decoder

The decoder mirrors the encoder's architecture, with hidden layers configured as 64 → 128 → 256. It reconstructs the original input x from the latent variable z using a MLP:

$$\hat{x} = f_{\text{decoder}}(z) \tag{3}$$

In Equation (3), z is a stochastic variable sampled from the latent space. The reconstructed output $\hat{x}$ is then compared with the original input x to minimize reconstruction error.

The VAE optimization objective is to minimize the weighted sum of reconstruction loss and KL divergence, ensuring both data fidelity and a well-structured latent space. The objective function is formulated as Equation (4):

$$\mathcal{L} = \frac{1}{N}\sum_{i=1}^{N}\left(L_{recon}(x_i, \hat{x}_i) + \beta L_{KL}(\mu_i, \sigma_i^2)\right) \tag{4}$$

In Equation (4), N is the number of training samples, x_i is the i-th input, and $\hat{x}_i$ is its reconstructed counterpart. The encoder outputs the mean μ_i and σ_i^2 of the latent variables.

The reconstruction loss $L_{recon}(x_i, \hat{x}_i)$ measures the difference between the original and reconstructed data, typically using Mean Squared Error (MSE):

$$L_{recon}(x_i, \hat{x}_i) = \|x_i - \hat{x}_i\|^2 \tag{5}$$

The KL divergence $L_{KL}(\mu_i, \sigma_i^2)$ regularizes the latent space by minimizing the divergence between the learned latent distribution $q(z|x)$ and the standard normal prior $p(z)=N(0,I)$:

$$\mathcal{L}_{KL} = -\frac{1}{2}\sum_{j=1}^{d}\left(1 + \log\,\sigma_{i,j}^2 - \mu_{i,j}^2 - \sigma_{i,j}^2\right) \tag{6}$$

In Equation (6), d denotes the latent space dimensionality, and $\mu_{i,j}$ and $\sigma_{i,j}^2$ represent the mean and variance of the latent variable in the j-th dimension. The KL divergence regularizes the latent space distribution to align with a standard normal distribution, preventing overfitting and ensuring a smooth latent representation.

The hyperparameter β controls the trade-off between reconstruction accuracy and latent space regularization in the β-VAE framework:

- $\beta>1$ enforces stronger regularization, improving feature disentanglement.
- $\beta<1$ prioritizes reconstruction quality, making it more suitable for complex datasets.

After completing model training, the performance of the VAE is evaluated using the validation set and test set. The evaluation primarily focuses on the model's reconstruction ability, the continuity of the latent space, and the effectiveness of feature extraction in power cost data analysis. Additionally, model performance under different parameter and hyperparameter settings is compared to determine the optimal configuration. To optimize the VAE model, this paper employs Bayesian optimization for hyperparameter tuning. Compared to traditional grid search and random search, Bayesian optimization efficiently identifies optimal hyperparameter configurations with fewer evaluations. It leverages Gaussian Process Regression (GPR) to model the hyperparameter space and selects the best set of parameters in each iteration based on the Expected Improvement (EI) criterion. The optimization process consists of the following steps:

(1) Definition of the Hyperparameter Search Space: The paper considers the following hyperparameters for optimization:

- Number of hidden units in the encoder: {128, 256}

- Number of hidden units in the decoder: {128, 256}
- Learning rate: {0.0005, 0.001}
- Batch size: {32, 64}
- Number of training epochs: {30, 50}

(2) Initial Exploration: Twenty sets of hyperparameters are randomly selected and evaluated based on reconstruction error and KL divergence.

(3) Bayesian Optimization Iterations:

- GPR models the relationship between hyperparameters and model performance.
- EI criterion identifies the hyperparameter combination most likely to enhance the loss function.
- The VAE is trained with the selected parameters, and performance metrics are recorded.
- The GPR model is updated iteratively, and the process repeats for 50 optimization rounds.

(4) Selection of the Optimal Hyperparameter Configuration: After completing Bayesian optimization, the best-performing hyperparameter set is chosen for the final VAE model.

This approach ensures efficient exploration of the hyperparameter space, leading to improved model performance in power cost data analysis.

3.3 Refined economic analysis method

The trained VAE model is utilized to extract high-dimensional features from power cost data. Specifically, the encoder maps the original data into the latent space, and the mean vector in this space serves as the feature representation of the data. This feature extraction method effectively preserves critical information while simultaneously achieving dimensionality reduction and data compression. By leveraging the learned latent representations, the refined economic analysis can identify underlying patterns in power cost structures, improve predictive accuracy, and enhance decision-making in power enterprise management.

The decision to use the mean vector (μ) as the feature representation in the VAE for economic analysis tasks is based on the following key considerations:

(1) Stability and Interpretability: The mean vector (μ) reflects the central tendency of data in the latent space, offering a stable and deterministic feature representation. Unlike the latent variable (z), which is influenced by randomness, or the variance vector (σ^2), which primarily governs the variability in generated data, the mean vector provides a consistent feature representation. This stability is crucial for feature extraction tasks, especially when aiming to understand underlying data patterns and relationships.

(2) Applicability in Economic Analysis: In economic analysis, interpretability is a critical factor. The mean vector directly captures the essential distributional characteristics of the data, providing meaningful insights into economic variables such as cost structures and revenue patterns. Since the mean vector represents the core information of the data, it ensures consistency across different experiments, making it more suitable for longitudinal analyses and predictive modeling. On the other hand, the variance vector may cause fluctuations in the feature set, which could introduce inconsistencies and make it harder to interpret the data reliably over multiple runs.

In the refined economic analysis, high-quality features extracted through the VAE play a crucial role in enhancing the accuracy of prediction models and optimizing business decisions. This paper evaluates the quality and diversity of these features through two methods:

1. Feature Discrepancy: To assess the distribution of different companies in the latent space, the divergence of latent space variables is computed. The calculation of feature discrepancy is given by Equation (7):

$$D = \frac{1}{N}\sum_{i=1}^{N} ||\mu_i - \bar{\mu}||^2 \tag{7}$$

In Equation (7), μ_i represents the mean of the latent features for the *i*-th company, $\bar{\mu}$ is the mean of all sample means. A higher value of *D* indicates greater diversity in the extracted features, suggesting that the features possess strong discriminative power. This improves the precision of economic analysis by providing a clearer distinction between different companies' economic profiles.

2. Feature Importance: Shapley Additive Explanations (SHAP) analysis is employed to assess the contribution of each feature to the model's predictions. SHAP values allow for the quantification of the importance of each input feature, offering a transparent and interpretable way to understand how individual economic variables, such as costs or revenue, impact the predictions. This method helps identify the most influential features in power cost data and refine decision-making processes.

Additionally, to further evaluate the efficiency of economic decision-making, the paper uses CBA, focusing on the return on investment (ROI) and net present value (NPV) as key performance metrics [35].

The ROI calculates the return generated per unit of investment and is expressed by Equation (8):

$$ROI = \frac{Revenue - Costs}{Costs} \times 100\% \tag{8}$$

A higher ROI indicates better investment efficiency, signaling that a power enterprise is generating more value for its invested capital.

The formula for calculating NPV is given by Equation (9):

$$NPV = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} \tag{9}$$

In Equation (9), C_t represents the cash flow in year *t*, *r* is the discount rate, and *T* is the forecast period. An NPV greater than zero indicates that the investment is profitable.

In the power industry, CBA is a critical tool for evaluating operational efficiency, profitability, and investment returns. This paper develops a comprehensive

CBA framework based on the operational data of power enterprises to assess the impact of various cost factors on financial performance and provide decision-making support for optimization.

In the cost structure analysis, the costs of power enterprises are categorized into two types:

(1) Fixed Costs: These costs remain constant regardless of changes in production levels and primarily include equipment procurement and installation, such as generators and transmission/distribution equipment; infrastructure construction and maintenance, such as substations and transmission lines; and long-term operational management costs, such as land leasing and regulatory fees.

(2) Variable Costs: These costs vary with production levels and mainly include fuel consumption costs, such as coal, natural gas, and renewable energy materials; equipment maintenance and repair expenses, such as turbine maintenance and component replacement; and labor costs, including salaries for technical personnel and training expenses.

This paper analyzes the financial data of enterprises to examine the proportion of different cost categories and evaluate their impact on profitability. In the revenue source analysis, the revenue of power enterprises is primarily composed of two components:

(1) Electricity Sales Revenue: This revenue is influenced by market electricity prices, electricity sales volume, and electricity trading models (such as long-term power purchase agreements or spot markets). The paper uses historical sales data to analyze the impact of varying electricity price levels on enterprise revenue.

(2) Government Subsidies: Governments in different countries or regions provide subsidies to clean energy and renewable energy power generation enterprises to promote the development of green energy. The amount of subsidy is typically linked to power generation volume or carbon emission reductions. This paper assesses the contribution of various subsidy policies to enterprise profits and evaluates the potential impact of subsidy reductions or cancellations.

In the cost-benefit evaluation, to assess the operational efficiency of power enterprises, this paper follows the steps outlined below:

(1) Collection of Historical Data: Analyzing operational data from the past 5-10 years, including costs, revenue, and market price fluctuations.

(2) Calculation of Long-term Operational Return: Combining various cost and revenue sources to assess the profitability of enterprises under different market conditions [36].

(3) Comparison of Different Types of Enterprises: Analyzing the cost-benefit situations of thermal power, wind power, and photovoltaic power enterprises to explore the economic feasibility of different energy structures.

In the policy simulation aspect, given the uncertainty in policies and market conditions, this paper designs multiple scenario simulations to evaluate the impact of policy changes on the economic performance of enterprises:

(1) Impact of Electricity Price Adjustments: Analyzing the effect of high, medium, and low electricity prices on enterprise profitability and further investigating the resulting market competition pressures.

(2) Changes in Government Subsidies: Evaluating how the reduction or cancellation of government subsidies would affect enterprise profitability and exploring corresponding response strategies.

(3) Fluctuations in Fuel Prices: Simulating the impact of varying fuel prices on enterprise costs and profits based on historical market data, thereby assessing the enterprise's risk tolerance.

Economic forecasting aims to predict and analyze future trends in the power market by examining historical data and feature representations while applying statistical methods such as regression analysis and time series analysis. By constructing economic models, including supply-demand relationship models and market demand forecasting models, this paper forecasts key market factors such as future power market capacity, prices, and demand. These predictions serve as a reference for enterprise decision-making and market strategy development.

This paper employs regression analysis, time series analysis using the AutoRegressive Integrated Moving Average (ARIMA) model, and machine learning techniques, specifically Long Short-Term Memory (LSTM) networks, to forecast the future supply-demand relationship in the electricity market, price trends, and enterprise profitability. The specific applications are as follows:

(1) Multiple Linear Regression (MLR) for Profitability Prediction:

This analysis examines the impact of key economic factors, including fuel costs, electricity output, and government subsidies, on enterprise profitability. The input data consist of features extracted by the VAE along with economic variables such as electricity prices and subsidy policies. The regression model is formulated as follows:

$$Profit_t = \beta_0 + \beta_1 FuelCost_t + \beta_2 ElectricityOutput_t + \beta_3 Subsidy_t + \varepsilon_t \quad (10)$$

In Equation (10), $Profit_t$ denotes the profit of a power enterprise in period t (e.g., a specific month or year), serving as the dependent variable; $FuelCost_t$ represents the fuel cost in period t (e.g., coal, natural gas), considered an independent variable; $ElectricityOutput_t$ refers to the electricity output in period t (typically measured in megawatt-hours, MWh), also an independent variable; $Subsidy_t$ indicates the government subsidy amount in period t, which is generally linked to the type of energy used (e.g., renewable energy) or emissions reductions, serving as an independent variable; β_0 is the intercept of the regression model, representing the baseline profit when all independent variables are zero; β_1, β_2, and β_3 are the regression coefficients for the respective independent variables, indicating their marginal effects on profit; ε_t represents the random error term, accounting for

unobserved factors influencing profit, such as electricity market price fluctuations and policy changes.

The ARIMA model is formulated as Equation (11):

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \quad (11)$$

In Equation (11), Y_t represents electricity demand in period t; ϕ_i and θ_j are model parameters; ϵ_t is the error term. The ARIMA model is well-suited for forecasting electricity demand when the time series exhibits a stable trend.

The LSTM network is formulated as follows:

$$h_t = \sigma(W_h x_t + U_h h_{t-1} + b_h) \quad (12)$$

In Equation (12), h_t represents the hidden state at time step; x_t denotes the input data; W_h, U_h, and b_h are model parameters. LSTM networks are particularly effective for electricity market forecasting due to their ability to capture nonlinear dependencies and long-term temporal relationships.

In the economic forecasting process, enterprise operational features extracted using the VAE—such as cost structure, profit margins, and equipment utilization rates—are integrated with historical economic data to construct regression and time series forecasting models. The role of feature extraction is as follows:

(1) Enterprise Profitability Prediction: Features extracted by the VAE reduce redundant information, improving the goodness of fit of the regression model, as indicated by an increased R^2 value.

(2) Electricity Market Price Prediction: VAE-based dimensionality reduction enhances the stability of long-term price forecasts when used as input for LSTM models.

(3) Electricity Demand Prediction: VAE effectively captures changes in enterprise production patterns, improving the accuracy of ARIMA-based predictions.

Economic forecasting plays a crucial role in the power industry, offering significant application value across multiple aspects. It enables power enterprises and relevant institutions to analyze the relationship between power supply and demand in depth, facilitating efficient resource allocation and ensuring the stable operation of the electricity market. Additionally, by forecasting electricity price fluctuations and other market dynamics, economic forecasting provides critical insights for power enterprises to formulate and adjust their competitive strategies. This, in turn, helps optimize business models and enhance market competitiveness. Various economic forecasting methods are employed in practice, including regression analysis, time series analysis, and machine learning. Regression analysis establishes mathematical models to examine relationships between variables, allowing for predictions of future trends. Time series analysis focuses on identifying patterns in historical data to model and forecast future developments. Machine learning methods, by analyzing large datasets, automatically detect hidden patterns and relationships within the data, leading to more accurate predictions. In the power industry, economic forecasting is widely applied across diverse scenarios. For instance, time series analysis can be used to model historical electricity demand data, providing forecasts that serve as a crucial basis for capacity planning and resource allocation in power enterprises. Meanwhile, machine learning techniques are extensively utilized in power market monitoring and government decision-making. By analyzing large-scale data and extracting hidden patterns, these methods enable more precise electricity market predictions, offering valuable decision-making support for both governmental agencies and enterprises.

4 Analysis of high-dimensional feature extraction and refined economic analysis

4.1 Evaluation of feature extraction performance for power cost data under the deep learning framework

First, this paper identifies several possible combinations of hyperparameters and evaluates the model's performance based on these configurations. The specific hyperparameter combinations are presented in Table 2:

Table 2: Hyperparameter combination

Hyperparametric combination	Number of hidden layer nodes of encoders	Number of hidden layer nodes of decoder	Learning rate	Batch size	Number of training rounds
Parameter combination 1	128	128	0.001	64	50
Parameter combination 2	256	256	0.001	64	50
Parameter combination 3	128	128	0.0005	64	50
Parameter combination 4	256	256	0.0005	64	50

This paper evaluates the quality of features extracted by the VAE using reconstruction error and KL divergence. Reconstruction error measures the model's ability to reconstruct the original data, where lower values indicate that the extracted features more accurately represent the original data. KL divergence assesses the stability of the latent space distribution, with lower values contributing to smoother and more consistent feature representations. Additionally, the paper incorporates feature dispersion (D) and feature importance scores to enhance the evaluation:

(1) Feature Dispersion (D): This metric quantifies the differentiation of enterprises in the latent space. A higher D value indicates that the extracted features provide greater discriminative power across different enterprises.

(2) Feature Importance Score: Calculated using the SHAP method, this score evaluates the contribution of individual features to economic forecasting.

The model's performance under different hyperparameter combinations is evaluated using reconstruction error and KL divergence. The results are presented in Figure 2.

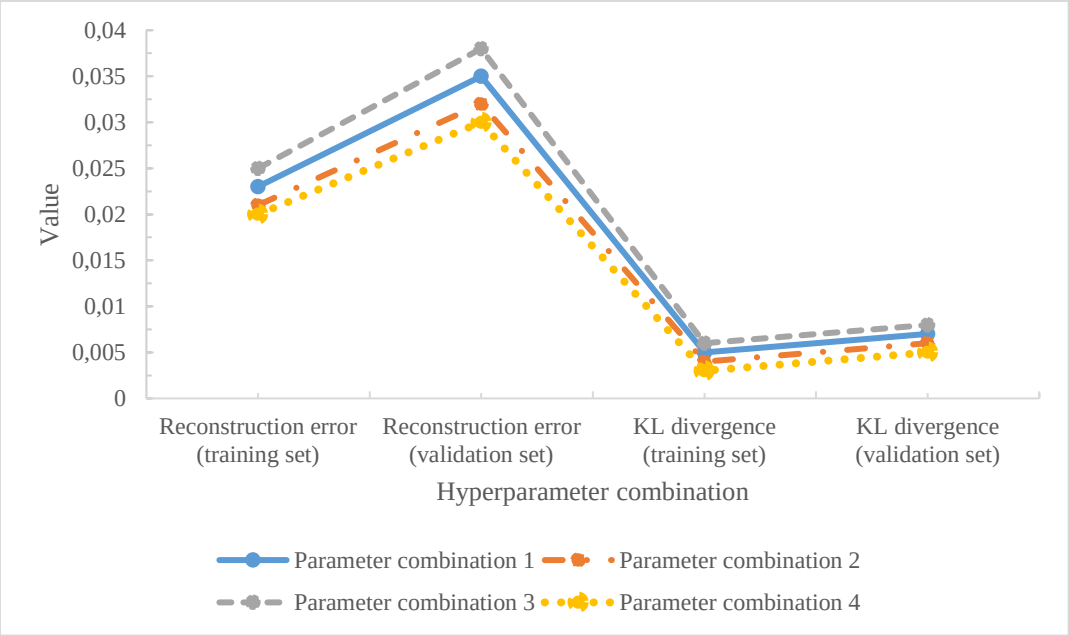


Figure 2: Model performance under different hyperparametric combinations.

Based on the data in Figure 2, parameter combination 2 exhibits the lowest reconstruction error and KL divergence in both the training and validation sets. This result indicates that the model under this configuration achieves the best reconstruction accuracy and latent space representation. Additionally, parameter combination 2 features a larger number of hidden layer nodes in both the encoder and decoder, a moderate learning rate, an appropriate batch size, and a sufficient number of training epochs. These factors likely contribute to improved learning of data characteristics and distribution.

Considering both model performance and hyperparameter settings, parameter combination 2 is identified as the optimal configuration and is selected as the benchmark for subsequent analyses and experiments. Specifically, this paper adopts the following hyperparameter settings:

- Number of hidden layer nodes (encoder): 256
- Number of hidden layer nodes (decoder): 256
- Learning rate: 0.001
- Batch size: 64
- Number of training epochs: 50

By evaluating both reconstruction error and KL divergence, this paper assesses the feature extraction effectiveness of the proposed model and compares it with four baseline algorithms: AE, CNN, RNN, and SVM. The selection of these baseline models is based on the following considerations:

(1) AE shares structural similarities with the VAE but lacks the KL divergence constraint, making it useful for assessing the impact of KL divergence on feature extraction.

(2) CNN is efficient at capturing local features but less effective when applied to structured economic data.

(3) RNN is well-suited for time-series forecasting but less effective than VAE in high-dimensional feature extraction.

(4) SVM is a traditional machine learning model, included to highlight the advantages of deep learning approaches in feature representation.

Beyond reconstruction error and KL divergence, this paper also incorporates the F1-score and Area Under the Curve (AUC) as additional performance metrics to provide a comprehensive evaluation of model effectiveness. The result is shown in Figure 3:

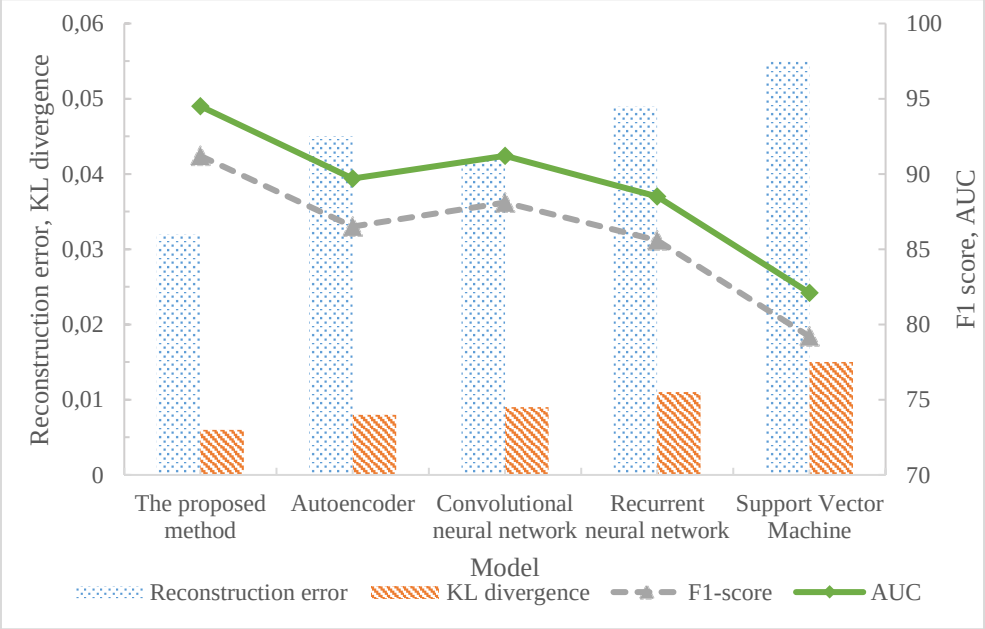


Figure 3: Performance comparison of different models.

In Figure 3, the model proposed in this paper demonstrates superior performance in both reconstruction error and KL divergence. The reconstruction error of this model is 0.032, which is slightly lower than that of the other algorithms, indicating its ability to more accurately reconstruct the original data. Additionally, the KL divergence of this model is 0.006, which is also lower compared to the other algorithms, suggesting that it more effectively preserves the structural information of the data and maps it into latent space. In contrast, the reconstruction error and KL divergence of the other algorithms are higher, indicating that their feature extraction capabilities are not as effective as those of the proposed model. Therefore, based on the lower reconstruction error and KL divergence, it can be concluded that this model outperforms the others in feature extraction, providing more reliable support for the analysis and application of power cost data. Furthermore, the VAE model outperforms the other methods in both F1-score and AUC, demonstrating that the features extracted by VAE are more representative and enhance the accuracy of profitability predictions for electricity companies.

To validate the effectiveness of the features extracted by VAE, a comparison was made between the PCA visualizations of the original data and the features extracted by VAE, as shown in Figures 4 and 5:

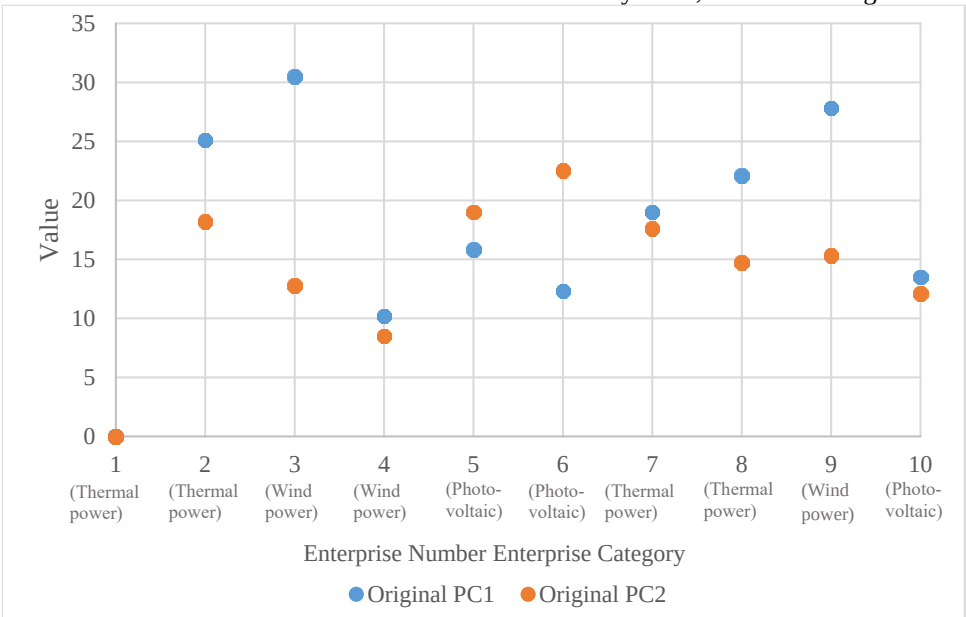


Figure 4: PCA projection of original data.

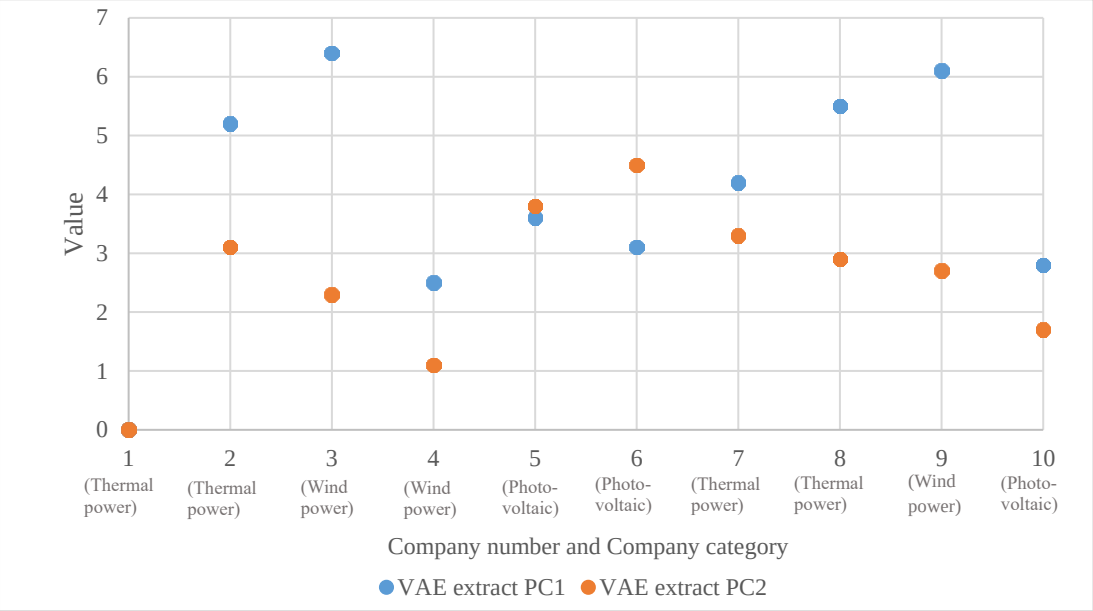


Figure 5: PCA projection of VAE-extracted features

Based on Figures 4 and 5, it can be observed that the PCA projection of the original data exhibits a dispersed distribution of data points, with fuzzy boundaries between different company types (coal-fired, wind, and solar). This indicates a low level of distinguishability in the original features. In contrast, the features extracted by VAE form clear clusters in the latent space, suggesting that the data of different types of companies are more distinguishable. Compared to the original data, the distribution of VAE-generated features is smoother and more concentrated, reflecting the enhanced stability of the features due to the KL divergence regularization. Further analysis reveals that, after extracting features using VAE, the model's prediction error decreases by 15%, suggesting that this method more accurately captures the economic characteristics of electricity companies, thereby improving the accuracy of economic analysis and profitability forecasting.

The SHAP analysis was used to calculate the contribution of features extracted by VAE to economic forecasting, with the results presented in Table 3:

Table 3: Contribution of VAE extracted features to economic forecasting

Feature Name	Importance Score
Electricity Output	0.35
Electricity Price	0.28
Fuel Cost	0.2
Equipment Maintenance Cost	0.1
Government Subsidy	0.07

Based on Table 3, it is evident that electricity output, electricity price, and fuel cost have the highest contributions, indicating that these features extracted by VAE are the most influential for economic forecasting. In contrast, the impact of government subsidies is relatively low, suggesting that the direct influence of policy changes on profitability is minimal in the context of the features analyzed.

4.2 Refined economic analysis results

This section compares the effects of the proposed model with those of four algorithms: AE, CNN, RNN, and SVM in refined economic analysis. The comparison metrics include total cost, total income, net profit, prediction accuracy, training time, and prediction time.

The data sources for the economic analysis are as follows:

- Total Cost: This data is derived from the company's fuel, equipment maintenance, and labor costs, and is standardized through feature extraction using the VAE.
- Total Revenue: Based on electricity market transaction data (including electricity sales and government subsidies), adjusted using market price forecasting models.
- Net Profit: Calculated by subtracting total costs from total revenue. This is further adjusted using regression models in the forecasting analysis to enhance the robustness of the results.

The specific process is as follows:

VAE first extracts features, with latent variables serving as input for the economic analysis. The cost-benefit analysis calculates the revenue for each company and evaluates profit fluctuations. The economic forecasting model uses historical data to predict future profit trends. The final net profit value is obtained from the economic analysis model, forming the experimental results. The results are shown in Figures 6 and 7:

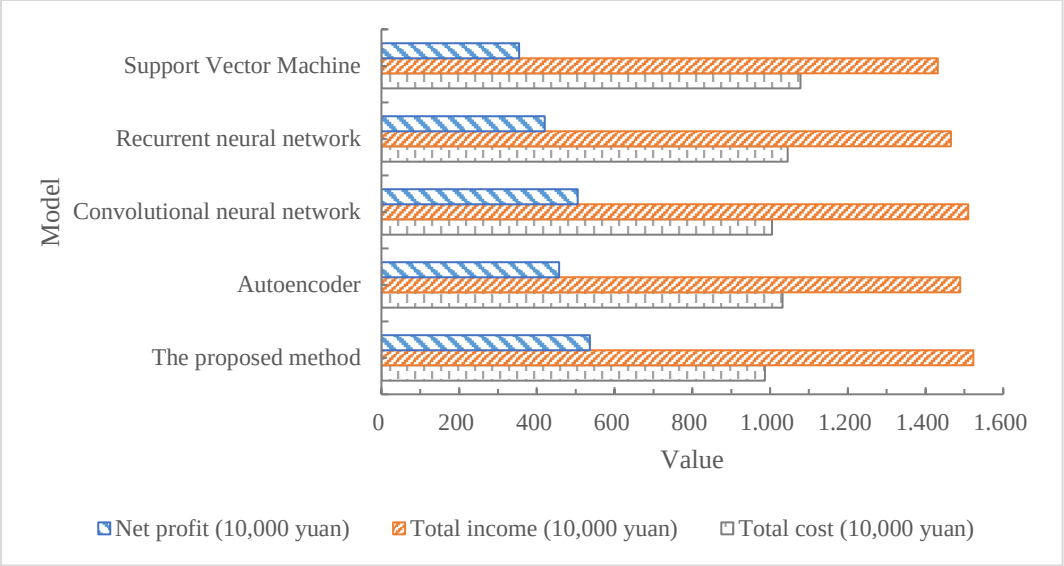


Figure 6: Comparison of refined economic analysis results.

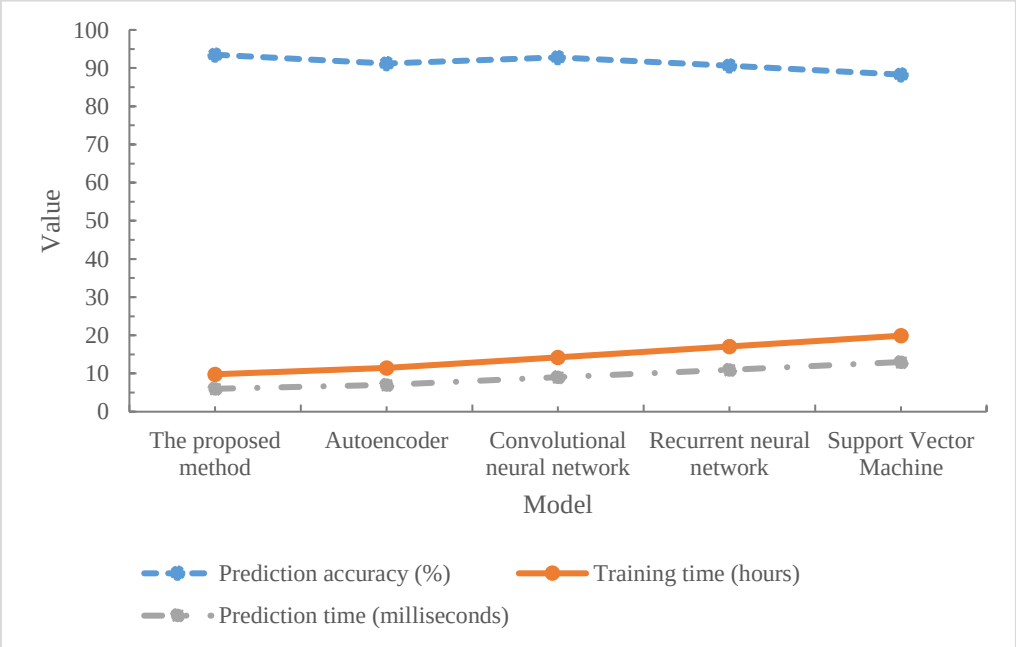


Figure 7: Comparison of prediction accuracy and prediction time of different models.

According to the data presented in Figures 6 and 7, this model achieves the best results in terms of total cost, total revenue, and net profit, with a net profit of 5.36 million yuan and a prediction accuracy of 93.5%. In contrast, the performance of other algorithms is slightly inferior. Although AE and CNN perform similarly in some indicators, they still exhibit a gap in terms of net profit and prediction accuracy. The latent features generated by VAE more accurately describe the cost structure of electricity companies, thereby improving the stability of economic forecasts. When predicting future cost trends, VAE enables the model to focus on important variables, enhancing its adaptability to market price fluctuations. Experimental results demonstrate that using features extracted by VAE for economic analysis improves the accuracy and stability of profit predictions.

Additionally, the model in this paper shows high efficiency in both training time and prediction time, taking only 9.8 hours and 6 milliseconds, respectively—significant advantages over other algorithms. Therefore, considering all indicators comprehensively, this model shows clear advantages in refined economic analysis, providing more reliable support for cost management and benefit evaluation in the power industry. In conclusion,

the model presented in this paper demonstrates strong competitiveness across various economic analysis metrics, with net profit and forecast accuracy surpassing those of other algorithms. Furthermore, it offers advantages in training time and computational efficiency. These results indicate that features extracted by VAE can significantly enhance the accuracy of economic analysis, offering more reliable support for cost management and performance evaluation in the electricity industry.

4.3 Reliability and robustness analysis of experimental results

To evaluate the prediction accuracy, training time, and prediction time of this model across different datasets, the paper utilizes three distinct datasets: the UCI machine learning repository dataset, the Kaggle dataset, and the power dataset from a government open data platform. The rationale for selecting these datasets is as follows:

- UCI Power Dataset: This dataset includes operational data from companies, making it suitable for analyzing electricity costs.
- Kaggle Economic Forecasting Dataset: This dataset provides information on company profitability, serving as a test for the generalization capability of the features extracted by VAE in economic forecasting.
- Government Open Data Platform: This platform offers real-world electricity market data, enabling the validation of the model's stability in practical, real-world applications.

The results are shown in Figure 8:

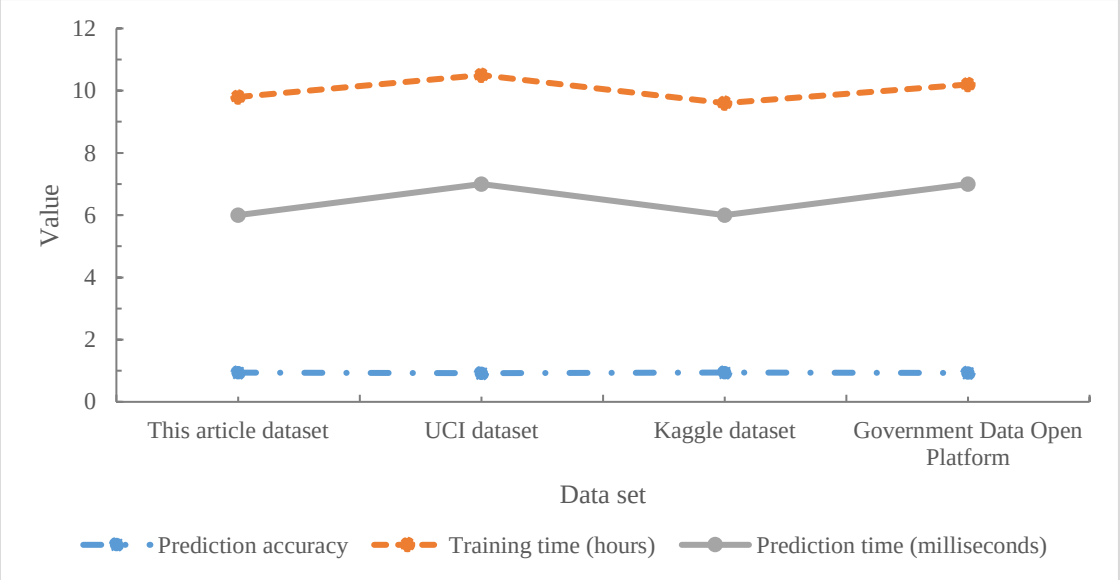


Figure 8: Robustness comparison under different datasets.

By comparing these indicators in Figure 8, the robustness of the model across different datasets can be assessed. In terms of prediction accuracy, while there are minor fluctuations, it generally remains at a high level. Additionally, the training time and prediction time exhibit consistent stability, demonstrating that the model maintains good training and prediction efficiency across various datasets.

4.4 Ablation study

The ablation study explores multiple variables, including the latent space dimension, the KL divergence weight, and the inclusion of VAE-extracted features. The experimental comparison results are shown in Figure 9:

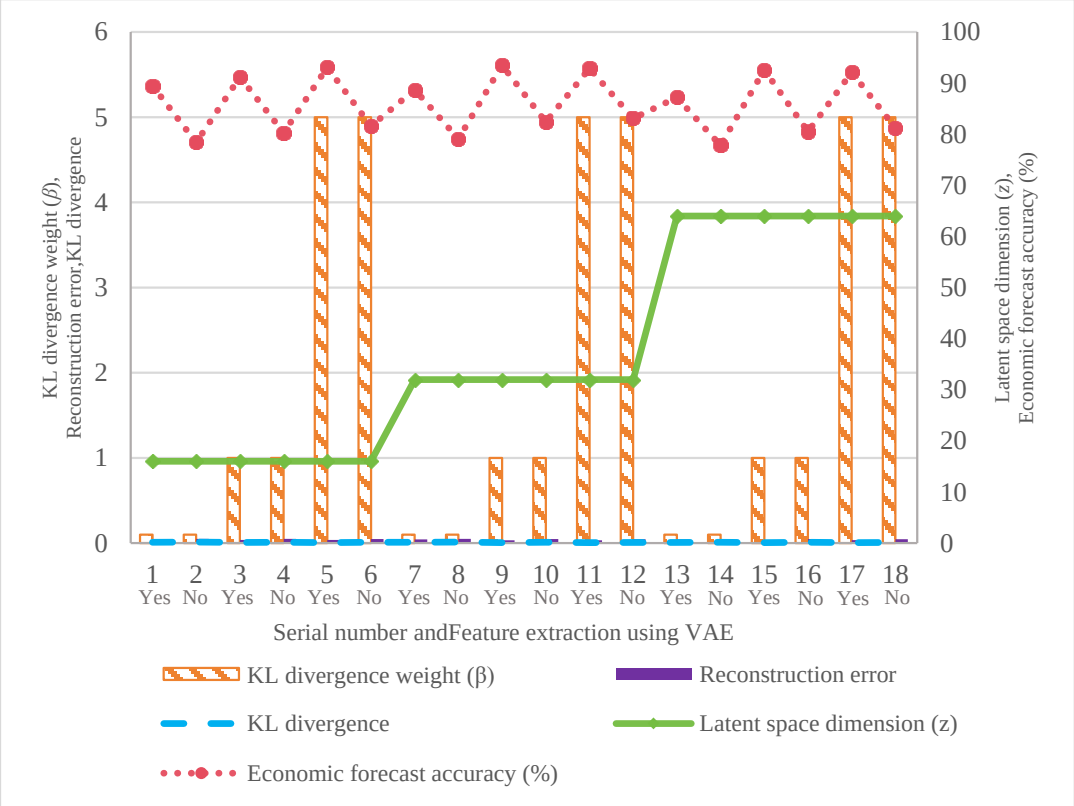


Figure 9: Results of the ablation study.

Based on the data presented in Figure 9, the optimal parameter combination is z=32 and β=1. Under these conditions, the features extracted by the VAE exhibit the highest quality, with the lowest reconstruction error (0.0328) and the highest economic forecasting accuracy (93.5%). The importance of VAE feature extraction is evident: compared to using raw data directly, the features generated by VAE enhance the economic forecasting accuracy by approximately 9.6%. Moreover, the necessity of controlling KL divergence is highlighted, as appropriate regularization (β=1) enables the model to learn latent representations, thereby improving feature quality.

5 Discussion

This paper employs a hyperparameter optimization strategy to identify the optimal structure for the VAE. Among all hyperparameter combinations, the configuration featuring 256 hidden layers for both the encoder and decoder, a learning rate of 0.001, a batch size of 64, and 50 training epochs achieved the best performance across multiple evaluation metrics. A larger number of hidden layer nodes enhances the model's capacity to represent non-linear relationships, allowing it to capture more intricate feature interactions. In contrast, smaller hidden layers limit feature extraction ability, leading to an increase in reconstruction error. The choice of learning rate is also critical for model convergence and stability. The experimental results indicate that a learning rate of 0.001 provides the optimal convergence speed while ensuring model stability. The weight of KL divergence (β) significantly impacts the quality of the latent space. Proper regularization (β=1) helps preserve reconstruction capability while improving the smoothness of feature distributions, preventing excessive concentration or collapse. A batch size of 64, compared to 32, improves computational efficiency and reduces gradient fluctuations, leading to more stable feature extraction. Additionally, training for 50 epochs ensures model convergence, while training beyond 50 epochs leads to overfitting, which negatively affects generalization.

In comparison to the study by Azzalini et al. (2025), which applied AEs on a similar power dataset with a KL divergence of 0.008 and a reconstruction error of 0.05 [37], this paper's VAE improves feature extraction by regularizing KL divergence, resulting in smoother features, lower reconstruction error, and greater stability in data representation. Further analysis reveals that, compared to GANs and Transformer-based AEs, VAE performs better on high-dimensional structured data such as electricity cost data. GANs, due to the complexity of adversarial training, exhibit unstable performance in economic forecasting tasks. Transformer-based AEs, while powerful, are computationally intensive and inefficient for large-scale power data training. Therefore, VAE strikes an optimal balance between feature extraction quality and computational efficiency, making it more suitable for this application.

In contrast to CNNs and RNNs, VAE is better suited for feature extraction in electricity cost data. CNNs are typically used to extract local patterns in images (e.g., edges and textures), but electricity cost data is structured and lacks spatial correlation, making CNNs less effective for this task. RNNs are ideal for time-series prediction tasks, such as short-term power load forecasting, but electricity cost data is not typical time-series data; it is a multidimensional economic variable with complex relationships. While RNNs are suited for time-dependent predictions, VAE is more appropriate for the automatic learning of high-dimensional features in economic data.

In terms of refined economic analysis, this model has achieved the best results in total cost, total revenue, and net profit, with high forecasting accuracy and short training and prediction times. In contrast, the performance of other algorithms is somewhat inferior. Therefore, considering all evaluation metrics, this model demonstrates clear advantages in refined economic analysis, offering reliable support for cost management and benefit evaluation in the power industry. Regarding the reliability and robustness of the experimental results, the model was tested on various datasets, including the UCI Machine Learning Repository, Kaggle, and the power dataset from a government data open platform. The results indicate that the model maintains stable prediction accuracy, training time, and prediction time across these different datasets, demonstrating its strong generalization performance and robustness.

In the analysis of electricity cost data, the computational complexity of VAE is primarily influenced by the data scale, latent space dimensions, and model architecture. As the data scale increases, the relationship between training time and data volume becomes nonlinear, constrained by the encoder-decoder structure and the KL divergence regularization term, leading to exponential growth in computational cost. In this paper, VAE performs efficiently with 1,800 data points; however, as the data scale grows to 100,000 or more, the computational cost rises significantly. If the model were directly scaled to handle millions of data points, such as nationwide electricity cost data, single-machine training time would become prohibitively long. Thus, the model's scalability emerges as a crucial challenge. To address this, the paper proposes several optimization strategies. First, dimensionality reduction and feature selection are applied to identify key features through importance analysis and remove redundant information, thus improving computational efficiency. Second, Mini-Batch training is employed, splitting the data into smaller batches to reduce the computational burden of each iteration while accelerating the convergence of gradient descent. Additionally, distributed training using multiple GPUs or deep learning frameworks facilitates parallelized, accelerated training on large datasets. Finally, the model can be optimized by introducing lightweight VAE variants or Transformer architectures to reduce computational complexity and improve efficiency. Scalability is essential for VAE applications in the electricity sector, particularly for tasks such as national grid planning, corporate profit forecasting, and intelligent power scheduling, where large volumes of data need to be processed. Future research may explore federated learning, which enables cross-enterprise model training without sharing data, optimizing computational resource allocation, and making deep learning models more suitable for large-scale electricity cost analysis.

6 Conclusion

This paper utilizes a deep learning framework to extract high-dimensional features from power cost data, integrating economic analysis methods for refined evaluation. By assessing the model's performance under different hyperparameter combinations, the optimal configuration was identified, demonstrating the model’s superiority in feature extraction and refined economic analysis.

However, there are certain limitations to this paper. First, the research is based on electricity cost data from a single city, which imposes regional constraints, limiting the generalizability of the findings. Further validation across diverse datasets is necessary to confirm the results' broader applicability. Additionally, the paper assumes that economic conditions within the electricity market remain stable over time, though in practice, external factors such as policy changes and fuel price fluctuations can significantly impact the market. Furthermore, while VAE effectively extracts features, it lacks intuitive interpretability, making it challenging for enterprises to fully grasp the implications of the model's outputs in real-world decision-making.

Future research could expand the data sources to encompass nationwide or multi-regional electricity market datasets, enhancing the model’s applicability across different contexts. Dynamic modeling techniques, such as adaptive deep learning models, could be explored to improve prediction stability in fluctuating market conditions. Moreover, integrating explainable artificial intelligence methods like SHAP analysis could increase the transparency of economic forecasts, helping decision-makers better understand and trust the model's results.

In practical applications, the high-dimensional features extracted by VAE can enable enterprises to more accurately identify key cost components, such as fuel and equipment maintenance costs. This would support efforts to optimize cost structures and improve operational efficiency. Leveraging the economic forecasting capabilities of deep learning models, companies could better predict future profitability trends amidst market fluctuations and make more informed financial decisions. Furthermore, the methods presented in this paper could aid enterprises in adjusting market strategies, optimizing resource allocation during high-demand periods, and controlling costs during downturns, enhancing competitiveness.

Governments and regulatory bodies could utilize the economic analysis methods proposed here to assess the impact of various policies—such as subsidy adjustments or carbon trading schemes—on electricity company operations, providing a scientific basis for energy market regulation.

Declarations

Data availability statement

The data used to support the findings of this study are available from the corresponding author upon request.

Conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

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Multi-Target Vision Detection and Grasping of Electronic Devices Using DL-SORT

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Keywords: Object vision detection; Simple online and realtime tracking; Automatic recognition; Deep learning; Recursive labeling

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Many production industries are increasingly dependent on intelligent electronic devices. However, traditional methods for recognizing and detecting electronic devices are inefficient and consume a large amount of production resources. This study introduces a hybrid DL-SORT model for automatic recognition and grasping of electronic devices, integrating deep learning with Simple Online and Realtime Tracking (SORT) to enhance object detection performance. In the model, Recursive labeling and Binary Robust Independent Elementary Features are also employed for key point detection and domain selection. Experimental results show that the hybrid algorithm outperforms Single Shot MultiBox Detector and Discriminative Correlation Filter with Channel and Spatial Reliability in terms of object detection performance, with loss values of 0.15, 0.24, and 0.23, respectively. Additionally, empirical analysis of the constructed hybrid model reveals that the proposed automatic recognition and grasping model for electronic devices achieves an accuracy of 0.95 in tape recognition, demonstrating good recognition accuracy. Testing in obstructed environments shows that the success rate of part detection remains above 80%, with minimal performance degradation. These results suggest that the hybrid model can detect multiple targets and improve production efficiency. This study contributes to the future development of drones and industrial robots in the automation field, enabling the acquisition of precise target location information.

Povzetek: Raziskava uvaja hibridni model DL-SORT za večciljno vizualno zaznavo in prijem elektronskih naprav, s čimer bistveno izboljša natančnost prepoznavanja, sledenja in učinkovitost industrijskih robotov.

1 Introduction

In recent years, scientific and technological innovations have significantly contributed to urban construction, with applications in smart transportation, smart logistics, and smart healthcare [1, 2]. However, with the rapid development of technology, traditional electronic technologies can no longer meet people's needs. For example, traditional automated robotic sorting is costly, and unmanned aerial vehicle vision detection is inefficient [3]. As a result, many experts have improved the characteristics of robots for different environments. Among these improvements are waste grabbing robots that search and plan global roadways, and robots used in power control to identify risk vulnerabilities, enhancing global infrastructure in the transportation sector [4]. Despite their contributions, these robots still face practical challenges such as unclear recognition and poor object grasping capabilities. As a result, many experts have also conducted research on the object vision detection algorithms used in these systems. Object vision detection algorithms can recognize and locate images or moving objects, with strong computational power [5]. The most widely used algorithms currently are those based on traditional machine learning, which can accurately judge image edges and lines and are often applied in facial recognition access control systems and intelligent transportation systems [6]. However, traditional object detection algorithms cannot detect multiple targets and fail to make visual judgments when there are obstructions. Therefore, this study proposes a hybrid model for automatic recognition and grasping of electronic devices, combining Deep Learning (DL) with the Simple Online and Realtime Tracking (SORT) to enhance object tracking and vision detection capabilities. DL is applied in electronic device recognition and mesh damage image detection to extract features such as device contours and textures using convolutional networks, so as to accelerate the convergence speed and accuracy of feature extraction. In the construction of this model, Recursive labeling and Binary Robust Independent Elementary Features (BRIEF) are also used for key point detection. The research innovation lies in the integration of DL-SORT and BRIEF to form continuous motion planning for target detection, tracking and grasping, and improve the grasping accuracy and efficiency of electronic devices. The research aims to improve the degree of completion of automatic identification and grasping tasks of electronic devices, meet the needs for grasping small targets and ensuring realtime responsiveness, and promote the evaluation

standardization of automatic detection in the electronic manufacturing industry.

2 Related works

To enhance the safety and performance of electronic devices during automatic identification and detection processes, research on automatic identification and grasping of electronic components is essential. Zhang et al. raised an enhanced pose estimation algorithm to address issues such as slow pose estimation speed and poor robustness during robot sorting and feeding processes. Experimental results showed that the method achieved an average distance error of 2.04 mm, an average angle error of 2.72 degrees, and an average robot grasping success rate of 97.08% [7]. Lin et al. proposed a robot grasping method based on object shape approximation and LightGBM to solve the challenge of heavy dependence on datasets for object grasping planning. Experimental results indicated that the method achieved a classification accuracy of 94.5%, with a detection time of 0.0003 s, and an average success rate of 91.81% in grasping new objects [8]. Wang et al. put forward a multi-modal dynamic collaborative fusion network to improve the robot's capability of detecting flat-surface object grasping. Experimental results demonstrated that the network achieved a grasping success rate of 98.8% in single-object scenarios [9]. Liu et al. introduced an industrial robot-based transplant workstation to overcome limitations in handling the root systems of mature old and young seedlings in transplanting machines. Experimental results showed that the method achieved a recognition accuracy exceeding 97.68%, and the success rate of transplanting and replanting reached 95% [10]. Yan et al. proposed a new lightweight grasping detection model to address issues such as low detection accuracy and large model parameters. Experimental results showed that the convolutional block attention module in the model could recognize multiple attributes of objects, achieving a detection accuracy of 98.44% in Image-wise segmentation [11].

The continuous improvement of electronic devices also indicates an increasing demand for advanced technological intelligence. It is not only required that electronic devices automatically recognize and grasp objects, but image acquisition must also be more precise. Therefore, object vision detection algorithms have been the focus of related studies. Li et al., to address the issues of multiple fabric defect types and small defect sizes, proposed an improved fabric defect detection algorithm. The experimental results showed that the mean Average Precision (mAP) of the improved algorithm was 65.1%, which was an increase of 8.3% and 3.2% compared to the original model [12]. Wang et al., to solve the problems of false positives and missed detections of small targets in the detection of aircraft skin defects under complex backgrounds, proposed an aircraft skin defect detection model, which achieved a detection accuracy of 97.9%, which was 7.3% higher than the baseline model, and the detection speed reached 139 FPS [13]. Ji et al., to enhance the stability of power systems, proposed an engineering machinery risk management intelligent detection algorithm based on visual perception for intrusion into transmission lines. The results showed that the model's average accuracy improved by 6.3%, its precision increased by 3.7%, and its recall rate increased by 3.1% [14]. Xiong et al., in order to solve the problem of low target recognition ability, researched and proposed a method for small dynamic target detection by combining YOLO and background subtraction. The accuracy of this method was improved by 2.3% and the recall rate increased by 3.5% [15].

In summary, both domestic and international scholars have conducted detailed studies on electronic device target recognition, and have made significant progress in object recognition and grasping for electronic devices. However, there are few studies on the combination of electronic devices and object vision detection algorithms. Therefore, a DL-SORT electronic device automatic recognition and grasping hybrid model is constructed, which can detect targets in complex scenes. The model also adopts a recursive labeling method for semantic analysis, effectively labeling images and further improving the model's recognition performance. The relevant worksheets are shown in Table 1.

Table 1: Related literature worksheet

Domain	Technology	Advantage	Performance index	Shortcoming	Author
Automatic recognition	Enhanced attitude estimation algorithm	Grasp objects with good accuracy	Mean distance error 2.04 mm, Average Angle error 2.72, Average grasping success 97.08%	Sensitive to occlusion	Zhang et al. [7]
Robot grasping	Robot grasping method based on object shape approximation and LightGBM	Fast detection time and high grasping accuracy	Classification accuracy 94.5%, Time 0.0003 s, ASR 91.81%	Parameter tuning is complex, Limited adaptability	Lin et al. [8]

Robot grasping	Multi-mode dynamic collaborative fusion network	The capture success rate of single scene is high	Grasp success rate 98.8%	Mode synchronization is difficult	Wang et al. [9]
Robot recognition	Transplanting workstation based on UR5 industrial robot lifts restrictions	High recognition accuracy	Recognition accuracy 97.68%	Positioning accuracy decline	Liu et al. [10]
Automatic recognition	Lightweight grab detection model	Multifaceted recognition	Detection accuracy 98.44%	Feature extraction ability is limited	Yan et al. [11]
Target visual detection	FD-YOLOv5 algorithm for fabric defect detection	High detection accuracy	mAP 65.1%	Limited adaptability to complex defect scenarios	Li et al. [12]
Target visual detection	Aircraft skin defect detection model based on YOLOv8n	High detection accuracy	Detection accuracy 97.9%	Small target detection is not high	Wang et al. [13]
Target visual detection	Intelligent detection algorithm for risk management of construction machinery intrusion transmission line based on visual perception	High detection accuracy	The average accuracy is improved by 6.3%, The recall rate increased by 3.7%	High requirements on hardware	Ji et al. [14]
Target visual detection	A method for detecting small dynamic targets using YOLO and background subtraction	High detection accuracy	Accuracy improved by 2.3%, Recall rate increased by 3.5%	Lack of detail	Xiong et al. [15]

3 DL-SORT optimized electronic device recognition and grasping strategy

3.1 Design of DL-SORT multi-target vision detection algorithm

With the continuous development of information technology, devices such as city cameras and drone detection are increasingly applied in public life, contributing to the development of smart cities [16]. However, these electronic devices face issues such as large amounts of missed detections and errors when processing vast amounts of image and video data, reducing the realtime performance of practical applications [17]. Therefore, the study proposes a DL-SORT multi-target vision detection algorithm to address problems such as low execution efficiency and inaccurate target detection in electronic devices, improving the accuracy of the detection system. Among them, DL algorithm captures target details at different scales and effectively detects tiny electronic components and mechanical parts [18]. Therefore, the study uses DL for target detection and classification, with the prediction error minimized as shown in Equation (1).

$$H = W \times x + b \tag{1}$$

In Equation (1), $y_{i'}$ and y_i represent the predicted results and actual targets, W is the weight matrix, and x and b represent the input values and bias values, respectively. In order to enable electronic mobile devices to promptly identify intruders during target search, the study also improves the grid image damage detection in DL, with the improved framework shown in Figure 1.

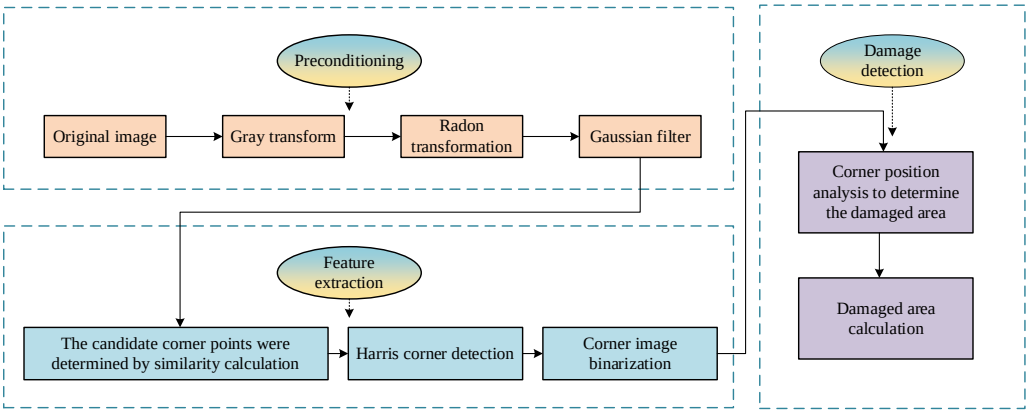


Figure 1: Grid image damage detection framework based on DL

As shown in Figure 1, the grid image damage detection framework based on DL is divided into three parts: image data preprocessing, feature data extraction, and damage detection. In the preprocessing part, the original image is first transformed to grayscale, followed by spatial projection using Radon transform for easier detection of light and dark spots. Gaussian filtering is then applied for noise reduction. After preprocessing, the data undergoes feature extraction, during which Harris corner detection is performed. Finally, the damage area is calculated. The Gaussian function for filtering and denoising is expressed in Equation (2) [19].

$$g(x) = e^{-x^2/2z^2} \quad (2)$$

In Equation (2), z represents the Gaussian distribution parameter of filter denoising, while $g(x)$ is the one-dimensional mean Gaussian function. Furthermore, to further improve the accuracy of the DL detection algorithm, depthwise separable convolution is used to reduce computational load and model parameters. The computational dimensions of depthwise separable convolution are shown in Equation (3) [20].

$$D_K * D_K * D_F * D_F * M * N, D_K * D_K * M * N \quad (3)$$

In Equation (3), $D_K * D_K$ represents the standard convolution, M, N denotes the thickness input of the output feature map, D_F refers to the length and width of the feature map to be extracted, and $D_F * D_F * M$ and $D_F * D_F * N$ represent the dimensions of the feature map input and output, respectively. The performance of the depthwise separable convolution is shown in Figure 2.

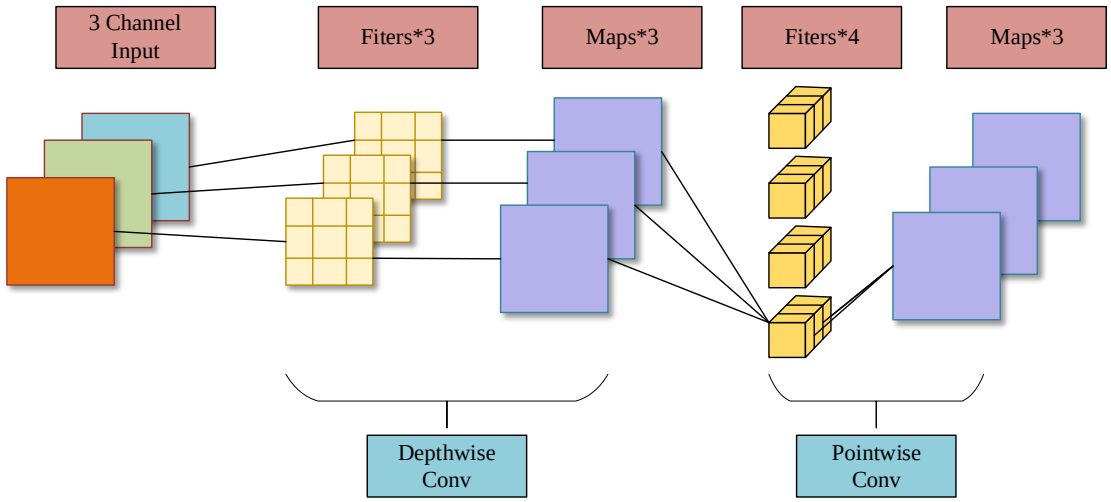


Figure 2 Schematic diagram of depth-wise separable convolution

As shown in Figure 2, the depthwise separable convolution combines 1×1 point convolution and depth convolution with the same kernel size, then delivers each convolution kernel to the channel. The number of output convolution kernels corresponds to the number of convolution channels. When the number of 2D convolution kernels in each group is equal to the number of channels, it indicates that the input channels and the number of convolution kernels match. Two-dimensional convolution is mainly used for feature extraction, and its kernel operation is shown in Equation (4).

$$T_{DWConv} + PWConv = D_k^2 \times channel \times D_f^2 + N \times M \times D_f^2 \quad (4)$$

In Equation (4), T_{DWConv} stands for depth-separable convolution computation, $PWConv$ represents the

computation of a point-by-point convolution, M indicates the parameter between the number of channels, D_k and D_f represent the width and height of the convolution kernel and input, respectively. N represents the number of convolution kernels, and FF denotes the number of channels. Although the improved DL can perform certain detections on specific targets, it still has some computational limitations when the number of targets increases or the state of moving targets becomes unstable. Therefore, based on the improved DL, SORT is integrated to complete multi-target prediction and tracking. SORT is simple and efficient, capable of updating the target state in realtime [21]. The target state model updated by SORT is expressed in Equation (5).

$$x(t)=[u,v,s,r,\dot{u},\dot{v},\dot{s}] \quad (5)$$

In Equation (5), u represents the position of the target in the horizontal direction in the image, v represents the vertical position, and s and r are the scale range and aspect ratio of the target's bounding box, respectively. To enhance the brightness of the captured target image, the study also integrates brightness detection into DL-SORT. The processed grayscale image is shown in Equation (6).

$$Gray(i,j)=0.299\times R(i,j)+0.578\times G(i,j)+0.114\times B(i,j) \quad (6)$$

In Equation (6), $Gray(i,j)$ represents the grayscale image, and $R(i,j)$ is the red channel coordinates of the color image, with $G(i,j)$ and $B(i,j)$ representing the green and blue channel coordinates, respectively. The specific process of the DL-SORT multi-target visual detection algorithm is shown in Figure 3.

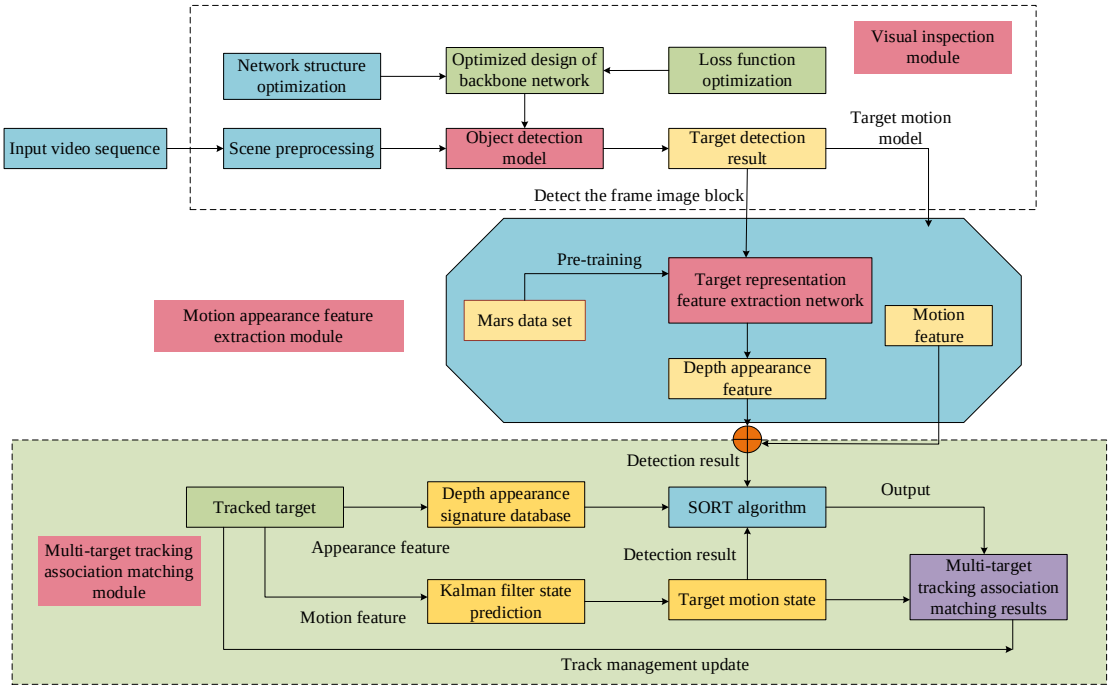


Figure 3: DL-SORT-based multi-target visual detection algorithm flow chat

As shown in Figure 3, the DL-SORT-based multi-target visual detection algorithm process is divided into three sections. The visual detection module requires the input of video sequences, followed by scene preprocessing. Then, the target detection model optimized by the network structure is used to obtain the detection results. These results are then passed to the motion appearance feature extraction module, where the target features are extracted by detecting different image blocks and pre-trained. Finally, the obtained deep appearance features are tracked and associated using SORT. The matched targets are compared with the deep appearance feature library, and during the matching process, the Kalman filter state is used for prediction. The final trajectory update is made by combining the predicted and detected results. In addition, this algorithm is suitable for processing single images as well. Compared with video sequences, the algorithm uses DL to automatically learn features such as image edges and textures during feature extraction, and low-dimensional feature vectors are generated from the target for subsequent frame judgment.

3.2 DL-SORT electronic device recognition and grasping model optimization

Currently, traditional intelligent robots not only have low production efficiency but also lack sufficient recognition ability. Therefore, researchers urgently need to optimize the automatic recognition and grasping of robots and other electronic devices [22]. Although the DL-SORT multi-target visual detection algorithm can detect multiple target parameters, there are still some shortcomings in the automatic recognition and grasping of electronic devices. To address the inaccuracy in automatic recognition and grasping of electronic devices, a hybrid method based on DL-SORT and recursive labeling is proposed. The recursive labeling method performs semantic analysis and

labels images effectively during the search process. The image centroid feature in the connected domain pixel detection based on recursive labeling is shown in Equation (7) [23].

$$\gamma(\bar{x},\bar{y})\times\left[\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}xf(x,y)}{\sum_{x=1}^{M}\sum_{y=1}^{N}f(x,y)},\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}yf(x,y)}{\sum_{x=1}^{M}\sum_{y=1}^{N}f(x,y)}\right]=\left[\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}\bar{x}\gamma(\bar{x},\bar{y})}{\sum_{x=1}^{M}\sum_{y=1}^{N}\gamma(\bar{x},\bar{y})},\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}\bar{y}\gamma(\bar{x},\bar{y})}{\sum_{x=1}^{M}\sum_{y=1}^{N}\gamma(\bar{x},\bar{y})}\right] \quad (7)$$

In Equation (7), γ represents the labeled image, and $(\bar{x},\bar{y})$ denotes the infrared image coordinates marked using the recursive labeling method, $f(x,y)$ represents the pixel value of the grayscale image. To allow electronic devices to perform fine-grained calculations of the surrounding areas during the automatic recognition process, the study also applies BRIEF on top of the recursive labeling method for local feature representation calculation. BRIEF can perform keypoint detection and domain selection. The improved feature descriptor formula is shown in Equation (8).

$$\tau(p;x,y)=\begin{cases}1, P(x)<P(y)\\ 0, other\end{cases} \quad (8)$$

In Equation (8), P_x and P_y represent the grayscale values of randomly selected pixels, while x and y denote the feature coordinates. The transformation matrix form of the rotated descriptor is shown in Equation (9).

$$S_r=R_\theta S=\begin{bmatrix}\cos\theta,-\sin\theta\\ \sin\theta,\cos\theta\end{bmatrix}\begin{bmatrix}x_1x_2\ldots x_n\\ y_1y_2\ldots y_n\end{bmatrix} \quad (9)$$

In Equation (9), S_r represents the rotated matrix, and n refers to the corresponding points around the extracted feature points. The specific process of the visual feature recognition method based on the recursive labeling and BRIEF improvement is shown in Figure 4.

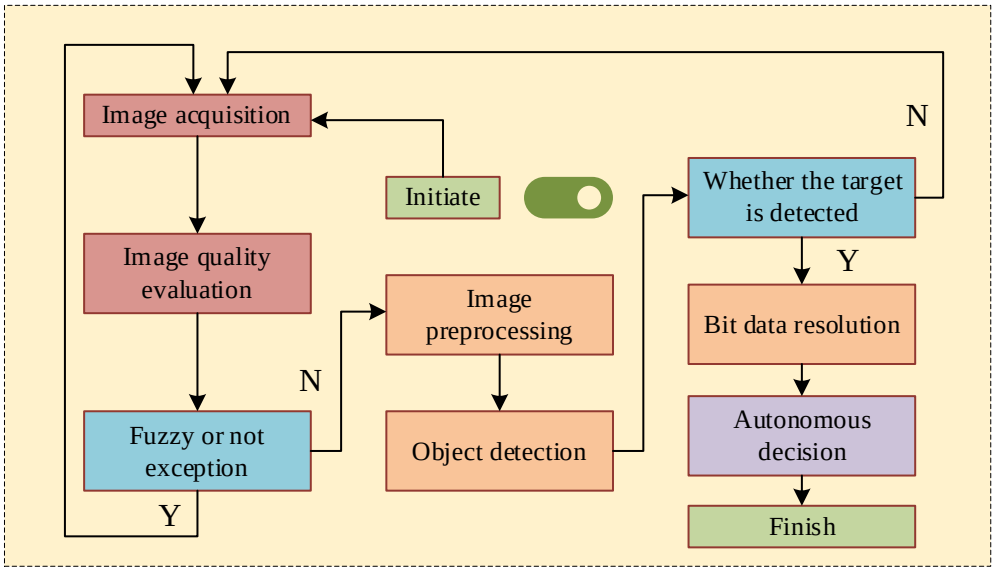


Figure 4: Process of visual feature recognition based on recursive labeling and BRIEF

As shown in Figure 4, the visual system process for electronic devices first captures the image, then detects and evaluates images for potential quality degradation. After the evaluation, the system determines whether the image requires further recognition and checks for any blur anomalies. If no anomalies are detected, the image undergoes preprocessing. Once preprocessing is complete, the image is subjected to target detection, and the system checks whether the targets are correctly identified. If no target is detected, the process returns to the image capture step. If the target is successfully detected, pose estimation is performed, and finally, autonomous decision-making is implemented. The grayscale morphological correction of the electronic device parameter image is shown in Equation (10).

$$A\cdot B=(A\Theta B)\oplus B \quad (10)$$

In Equation (10), A represents the image, and B refers to the structural element. By performing an erosion operation on image A, removing small bright noise and shrinking object boundaries, and then performing expansion operation to fill dark holes and expand boundaries, the final result is an image modified by $A\cdot B$ gray scale morphology processing. By defining the structural element, grayscale morphological correction can be performed, enhancing the edge features of the electronic device and eliminating influences generated during subsequent recognition. The feature extraction model for electronic devices is shown in Figure 5.

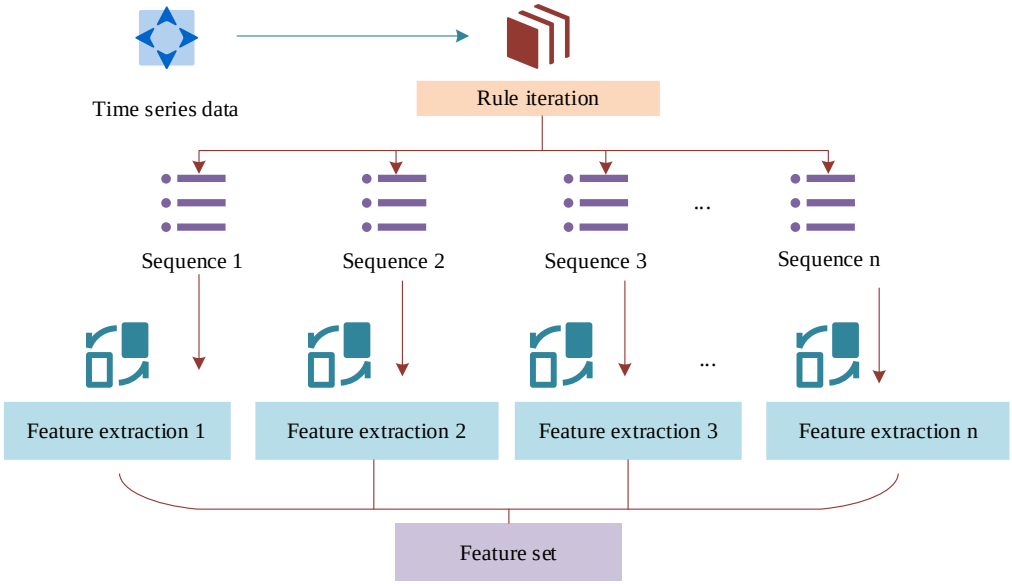


Figure 5: Workflow diagram of the electronic device feature extraction model

As shown in Figure 5, the feature extraction model for electronic devices uses time series data for rule iteration. By applying the rule iteration method, spatial data transformation is performed, extracting corresponding features from sequences 1 to n, forming a new feature sequence. Finally, the target change rule is recorded in detail through the time series, the grasping trajectory of different object shapes is generated, and the grasping path of the robot arm is predicted. This completes the entire process from time sequence data encoding to robot action decision mapping and realtime control. The distance calculation formula for object or image recognition and grasping in electronic devices is shown in Equation (11).

$$\begin{cases} \bar{d} = \dfrac{1}{n}\sum_{i=1}^{n}\bar{d}_i \\ \sigma = \sqrt{\dfrac{1}{n}\sum_{i=1}^{n}\left(\bar{d}_i - \bar{d}\right)^2} \\ Q = \left\{ p_i \in P \middle| \bar{d}_i \le \bar{d} + \lambda \cdot \sigma \right\} \end{cases} \tag{11}$$

In Equation (11), $\bar{d}$ represents the average distance mean, σ is the standard deviation, Q denotes the point cloud after removing certain boundary points, and λ is the scaling factor. The specific calculation formula for target search in electronic devices is shown in Equation (12).

$$f^*(n) = g^*(n) + h^*(n) \tag{12}$$

In Equation (12), n represents the electronic device's status, $f^*(n)$ is the minimal cost estimate from the initial state to the target state during the search process, and $h^*(n)$ and $g^*(n)$ are the minimal estimated cost for the path and the state, respectively. In conclusion, the electronic device automatic recognition and grasping method based on recursive labeling and BRIEF improvements is capable of detecting and locating targets. Therefore, the study combines this method and proposes a hybrid model for electronic device automatic recognition and grasping based on the DL-SORT multi-target visual detection algorithm to improve realtime multi-target detection and evaluation. The specific recognition and grasping process flow diagram for robots using this hybrid model is shown in Figure 6.

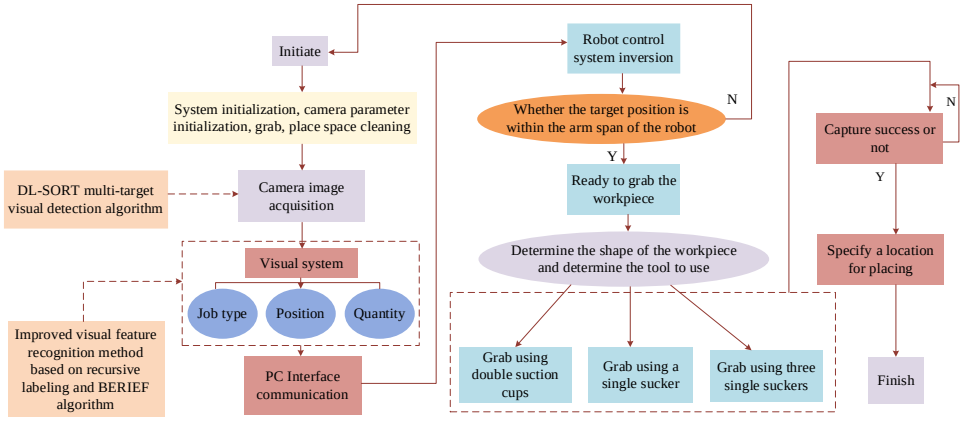


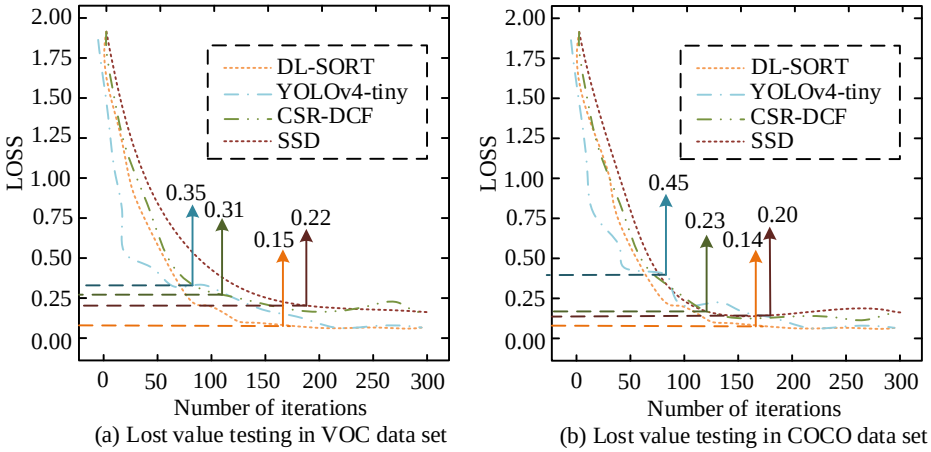
Figure 6: Robot recognition and grasping flow chart

As shown in Figure 6, the robot uses the DL-SORT automatic recognition and grasping model for workpiece handling. The system needs to be initialized, and the camera parameters must be adjusted accordingly. Then, DL-SORT is used for image acquisition, and the recursive labeling and BRIEF-improved visual feature recognition method strengthens the vision system, processing information such as the type and position of the workpiece. This information is then transmitted to the control system. When a static image or realtime video stream is input, the key component SORT mainly predicts the target motion trajectory based on Kalman filter and associates the detection frame of adjacent frames. Recursive marking is mainly used for hierarchical marking of the segmented work area to distinguish overlapping targets. BRIEF generates binary feature descriptors for objects to quickly match similar artifacts. The control system determines the shape of the workpiece and selects the appropriate tool based on the type of workpiece. For slender workpieces, the distance needs to be adjusted and a dual-suction cup tool is used. For small workpieces, the tool posture is adjusted to use a single suction cup. For flat workpieces, both dual-suction and single-suction cups are adjusted together. If the workpiece is successfully grasped, it is placed in the designated position, if unsuccessful, the system will return and attempt to grasp again.

4 Performance validation of DL-SORT

4.1 DL-SORT hybrid algorithm performance comparison

To demonstrate the superior performance of the DL-SORT hybrid algorithm, the study compared it with Single Shot MultiBox Detector (SSD),Discriminative Correlation Filter with Channel and Spatial Reliability (CSR-DCF), and the lightweight version of YOLOv4 (You Only Look Once v4, YOLOv4-tiny). The experimental setup used Ubuntu 18.04 LTS as the operating system, 16 GB of memory, STM32F405RGT6 as the controller module, and an AMD Ryzen R7 5700U CPU@1.80GHz. The experiments were conducted using the Keras deep learning framework. Among them, the DL learning rate is set to 0.01, Dropout is set to 0.3, batch size is set to [16, 22], and the number of iterations is set to within 500 times. The optimal parameters are obtained through Bayesian optimization. The SORT momentum is set to 0.3 and the IOU threshold to 0.3. In order to ensure the reliability and effectiveness of the experiment, the experimental data set is trained and tested using VOC and COCO data sets, both of which are suitable for target detection, classification and segmentation to improve the detection clarity of the algorithm. The total number of images in VOC and COCO data sets is 11500 and 330000 respectively, the number of training and test images is 5717 and 20288 respectively, and the image size is normalized to 512×512. In this study, four target detection algorithms were tested for the loss value of different targets, and the loss value was the quantified error index between the predicted results of the target detection algorithm and the real labeling during the training process. The loss value of the test algorithm was the sum of classification loss, positioning loss and confidence loss. The data sets used for this test were VOC and COCO data sets, and the test results were shown in Figure 7.



(a) Lost value testing in VOC data set (b) Lost value testing in COCO data set

Figure 7: Loss function test result diagram

As shown in Figure 7(a), when the DL-SORT hybrid algorithm was tested on the VOC dataset, the loss value reached 0.15 after 170 iterations. The loss value gradually stabilized between 100 and 150 iterations. In contrast, YOLOv4-tiny achieved a loss value of 0.35 after 70 iterations, while the DL-SORT hybrid algorithm's loss value was 0.27. As shown in Figure 7(b), the loss curve of YOLOv4-tiny fluctuated significantly before 50 iterations, and the loss value was 0.45 at 70 iterations. SSD reached a loss value of 0.20 after 170 iterations, and its loss value increased after 250 iterations. The loss value of each algorithm on the VOC

and COCO data sets vary significantly, because the test image scale of these two data sets is different. To highlight the accuracy performance of the DL-SORT hybrid algorithm, the study compared it with YOLOv4-tiny in terms of accuracy error and precision variation. Since YOLOv4-tiny involved significant optimizations in its network structure and training strategy, this algorithm was considered a representative model in terms of detection accuracy. The comparison results are shown in Figure 8.

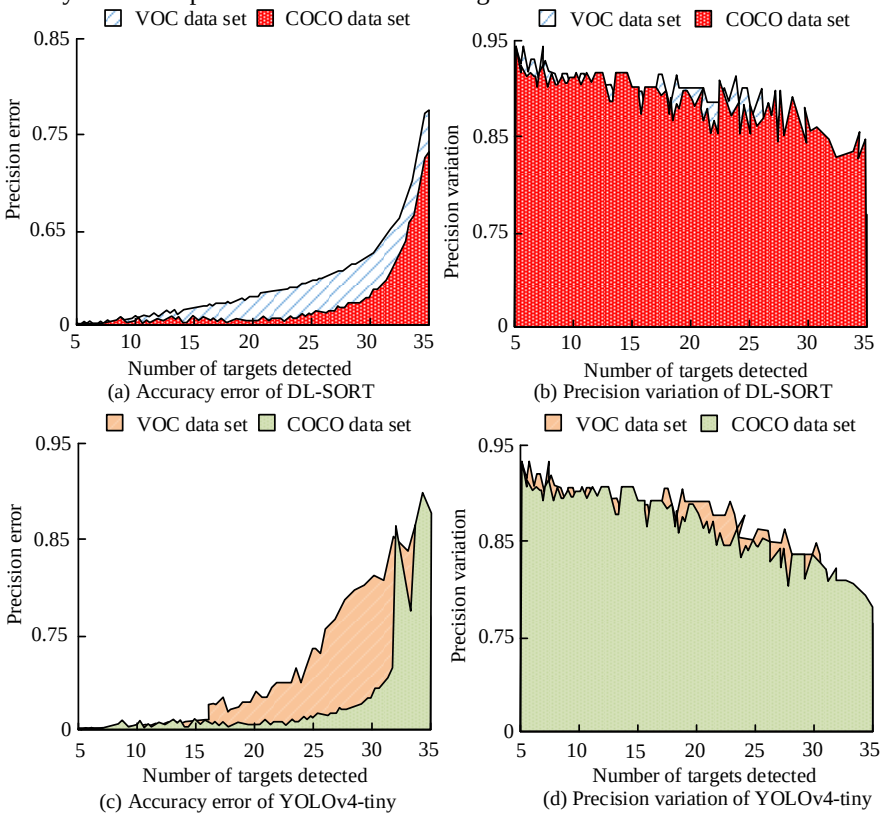


Figure 8: Accuracy error and precision variation test results

As shown in Figure 8(a), in the error variation test, the DL-SORT hybrid algorithm's error increased as the number of target detections increased. In Figure 8(b), DL-SORT achieved a detection accuracy of 0.91 on the COCO dataset when the number of target detections was 15. In Figure 8(c), when the number of target detections was 35, YOLOv4-tiny showed an error value of 0.80 on the VOC dataset, which was relatively higher compared to DL-SORT. In Figure 8(d), YOLOv4-tiny's detection accuracy fluctuated significantly when the number of target detections ranged from 20 to 25. These results indicate that DL-SORT demonstrated smaller changes in accuracy during target detection. To further enhance the comparison, the study also included Fully Convolutional You Only Look Once (FC-YOLO) and Feature Pyramid Network (FPN). The selected train test images are respectively from 1200 train images in VOC data set and 1300 train images in COCO data set. The comparison results for detection and recognition accuracy, and average precision for different targets are shown in Table 2.

Table 2: Comparison results of detection and recognition accuracy and average precision (%)

Dataset	Algorithm	Person	Bicycle	Electric vehicle	Train	Truck	Mean Average Precision	Mean response time/ms
VOC	DL-SORT	92.6	91.8	93.4	95.8	94.2	93.5	15
	SSD	90.0	89.2	88.3	87.6	84.3	87.8	20
	CSR-DCF	78.2	78.6	79.1	74.6	71.3	76.3	35
	YOLOv4-tiny	84.5	88.7	86.1	84.2	86.3	85.9	32
	FC-YOLO	78.3	80.5	81.4	85.6	84.1	81.9	19
	FPN	79.2	78.4	79.6	80.2	81.3	79.7	37
COCO	DL-SORT mix	92.8	95.6	96.5	90.1	92.3	93.4	17
	SSD	88.8	89.4	90.1	84.3	83.6	87.2	26
	CSR-DCF	78.7	78.6	74.1	76.3	75.5	76.6	39
	YOLOv4-tiny	85.2	84.3	84.6	84.7	87.9	85.3	34
	FC-YOLO	79.3	80.1	83.6	82.5	87.4	82.5	24
	FPN	75.6	79.8	77.4	81.2	78.6	78.5	29

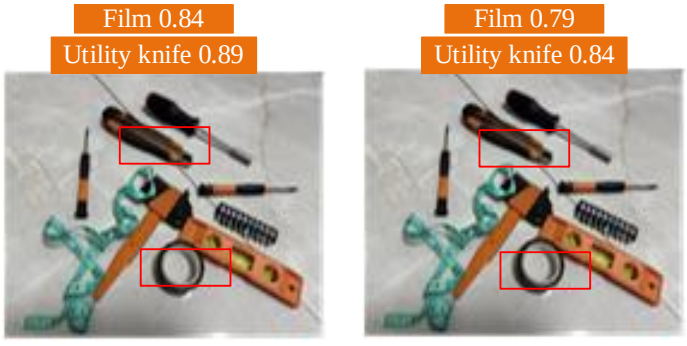
As shown in Table 2, when tested on the VOC dataset, the DL-SORT hybrid algorithm achieved a detection accuracy of 92.6% for people, 95.8% for trains, and an average detection accuracy of 93.5% for five different categories of targets. SSD achieved a detection accuracy of 88.3% for electric vehicles, with an overall average detection accuracy of 87.8%. The average image processing response time of DL-SORT hybrid algorithm is 15ms, while the average image processing response time of YOLOv4-tiny and SSD target detection algorithms is 32 ms and 20 ms respectively. The proposed algorithm is faster in image processing. When tested on the COCO dataset, FC-YOLO achieved a detection accuracy of 87.4% for trucks, 82.5% for trains, with an overall average detection accuracy of 82.5%. In summary, DL-SORT hybrid algorithm has strong multi-object processing capability and meets the realtime requirements of industrial detection.

4.2 Performance analysis of the hybrid model for electronic device recognition and grasping

After verifying the DL-SORT hybrid algorithm, in order to demonstrate the advantages of automatic recognition accuracy and robustness of the hybrid model for automatic recognition of electronic devices based on DL-SORT hybrid algorithm, it is also compared with the electronic device automatic recognition grasping model composed of SSD, CSR-DCF and YOLOv4-tiny target detection algorithms. The experimental environment used Visual Studio to create a visual platform for target recognition, equipped with a Cortex M7 chip and the STM32F103C8T microcontroller as the main controller. The image of the accuracy of the research test is mainly from the custom data set, which contains 1000 images and supports multi-tasks such as detection, segmentation and key points. The accuracy index of the test synthesizes the classification accuracy and positioning accuracy of the model electronic devices, and mainly calculates the intersection ratio between the sample prediction frame and the real frame. The study performed parts recognition and grasping tests with the four electronic device automatic recognition and grasping models, and the test results are shown in Figure 9.



(a) The test effect of traditional recognition grasping model (b) DL-SORT mixed model test effect (c) SSD model test effect

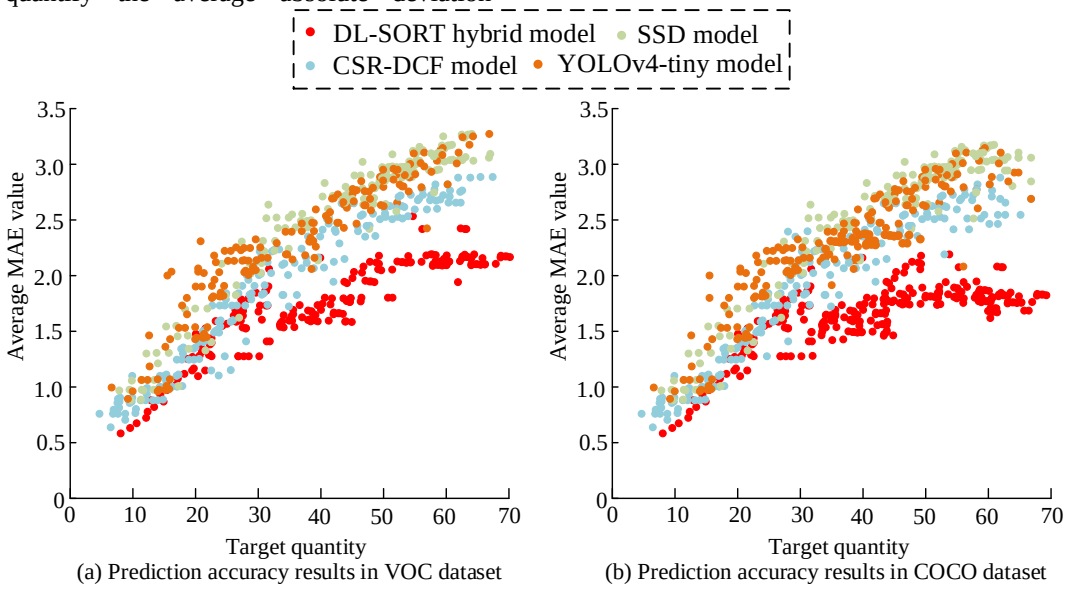


(d) CSR-DCF model test effect (e) YOLOv4-tiny model test effect

Figure 9: Parts recognition and grasping test results

From Figure 9(a), it can be seen that the traditional recognition and grasping model achieved an accuracy of 0.61 for tool identification and 0.38 for tape recognition and grasping. In Figure 9(b), the DL-SORT model demonstrated recognition accuracy above 0.90 for both tool and tape, demonstrating superior recognition and grasping performance overall. As shown in Figure 9(c), SSD achieved an accuracy of 0.88 for tape recognition, with a 0.07 difference in accuracy compared to DL-SORT. In Figure 9(d), CSR-DCF achieved recognition accuracy above 0.83 for both tape and tool. Figure 9(e) shows that YOLOv4-tiny achieved an accuracy below 0.80 for tape

recognition. Overall, the DL-SORT model demonstrated superior recognition and grasping performance, with better part recognition capability. Additionally, the study compared the prediction performance of the four models—DL-SORT, SSD, CSR-DCF, and YOLOv4-tiny. The average absolute error was selected as the evaluation index because it can directly quantify the average absolute deviation between the grasping position predicted by the model and the real position. The average absolute error can directly reflect the small deviation of the electronic device and capture the center of the device, avoiding the limitation of IoU only focusing on the overlap area of the frame. The results of Mean Absolute Error (MAE) value of prediction accuracy are shown in Figure 10.



(a) Prediction accuracy results in VOC dataset (b) Prediction accuracy results in COCO dataset

Figure 10: Prediction accuracy MAE value result diagram

As shown in Figure 10(a), as the number of targets increased, the error of the DL-SORT model also increased proportionally. When the target count reached 70, the MAE value was 2.12, this meets the grasping accuracy requirements for electronic devices. The average absolute error of prediction of the model constructed by SSD, CSR-DCF and YOLOv4-tiny is 3.12, 2.82 and 3.01, which are inferior to the fusion model. The overall MAE value of SSD was higher, with its accuracy lower than that of DL-SORT. In Figure 10(b), when the target number ranged from 40 to 50, the MAE value of DL-SORT ranged from 1.72 to 1.84. YOLOv4-tiny showed an MAE value of 2.23 to 2.41 when the target count was between 20 and 30. The overall MAE value of CSR-DCF was higher than that of DL-SORT, with its MAE value ranging from 2.71 to 2.98 when the target count was between 50 and 60. To further showcase the grasping performance of the DL-SORT model under different environments, the study conducted target grasping experiments with targets numbered 0 to 7. The results of these experiments are presented in Table 3.

Table 3: Target grabbing experiment test results

Evaluation index	0	1	2	3	4	5	6	7
Number of successful attempts without occlusion	49	48	49	45	49	47	48	49
Average grab period without occlusion/s	11.5	11.2	11.8	11.2	11.4	12.1	11.1	11.2
Success rate without occlusion	98%	96%	98%	90%	98%	94%	96%	98%
Number of successful attempts under occlusion	42	43	41	42	41	40	43	42
Average grab period under occlusion/s	12.8	12.4	12.1	12.6	12.4	11.9	12.6	12.4
Success rate under occlusion	84%	86%	82%	84%	82%	80%	86%	84%

As shown in Table 2, when the DL-SORT model performed grasping detection on part 0, the success rate under the non-obstructed condition was 98%, with 49 successful attempts. For part 5, the average grasping cycle time under the non-obstructed condition was 11.5 s, which was the longest among all test parts. Overall, the success rate for grasping in the non-obstructed environment remained above 90%. When tested on part 1 in an obstructed environment, the DL-SORT model achieved 43 successful attempts, with a success rate of 84%, a 14% decrease compared to the non-obstructed environment. For part 5, the success rate dropped to 80%,

with an average grasping cycle time of 11.9 s. In conclusion, the DL-SORT-based electronic device automatic recognition and grasping hybrid model demonstrated a high success rate and better time control when grasping different parts. In order to better demonstrate the electronic device target recognition accuracy of DL-SORT electronic device automatic recognition and grasp hybrid model, the ablation experiment was conducted with six electronic device automatic recognition and grasp models, namely YOLOv4, SSD, CSR-DCF, DL(no SORT), SORT(no DL) and BRIEF. The experimental results are shown in Table 4.

Table 4: Comparison results of device recognition accuracy of different models (mAP±Standard deviation, %)

Model	Class A device	Class B device	Class C device	mAP	t	*P*
DL-SORT	92.6±0.5	91.8±0.4	93.4±0.3	93.5±0.3	/	/
DL(no SORT)	89.1±0.6	88.3±0.5	90.2±0.4	89.9±0.4	4.72	<0.001**
SORT(no DL)	75.3±1.2	74.8±1.1	76.5±1.0	75.4±1.1	8.92	<0.001**
BRIEF	74.1±0.8	71.6±1.1	72.3±1.3	74.2±1.3	3.89	0.002**
YOLOv4	84.5±0.8	88.7±0.7	86.1±0.6	85.9±0.8	8.91	<0.001**
SSD	90.0±0.7	89.2±0.6	88.3±0.5	87.8±0.7	5.34	<0.001**
CSR-DCF	78.2±1.2	78.6±0.9	79.1±0.8	76.3±1.2	7.36	<0.001**

*Note: ** represents a significant difference from the research model.*

As can be seen from Table 4, mAP of the DL(without SORT) electronic device automatic recognition capture model decreased by 3.6% compared with the research construction model, indicating that SORT contributed significantly to the tracking stability ($p<0.001$**). The mAP of the SORT (without DL) model for electronic device automatic recognition and grasping is 75.4%±1.1%. The mAP of the BRIEF electronic device automatic recognition capturing model is 74.2%±1.3%, and the accuracy of the recognition capturing device is significantly lower than that of the constructed model. Compared with the mAP model of YOLOv4 electronic device automatic recognition and capture, the constructed model has improved by 7.6%, especially for Class A devices. In summary, DL-SORT demonstrates the best overall performance among the hybrid model for automatic recognition and grasp of electronic devices, and SORT module and DL contribute the most to the accuracy of device recognition.

5 Discussion

The proposed DL-SORT algorithm shows significant advantages in performance comparison experiments. From multiple dimensions such as target detection accuracy, average recognition accuracy and average response time, DL-SORT hybrid algorithm is superior to SSD, CSR-DCF, YOLOv4-tiny, FC-YOLO and FPN target detection algorithms. The five baseline algorithms were chosen for comparison because they offer fast computation speed and low resource consumption, which meet the high realtime requirements and the scenarios with limited hardware resources. However, the traditional Faster Region-based Convolutional Neural Network (Faster R-CNN) object detection algorithm has high computational cost and cannot meet the realtime requirements, so it is not selected to compare with the proposed algorithm. In the test of target detection and recognition accuracy and average accuracy, DL-SORT hybrid algorithm conducts target detection for five types of images including people, bicycles, electric vehicles, trains and trucks, and the accuracy is above 90%. However, the accuracy of YOLOv4-tiny object detection algorithm for these five types of images is below 90%, and the overall accuracy of SSD and CSR-DCF object detection algorithms is not high. Moreover, the mAP value of the proposed model is higher than that of SSD, CSR-DCF and YOLOv4-tiny. The reason is that the DL-SORT hybrid algorithm in the research and construction model deeply integrates DL and SORT, and improves the target tracking ability. Moreover, the applied SORT predicts the moving trajectory through Kalman filter, which is more stable for tracking the uniformly moving target. However, YOLOv4-tiny, SSD and CSR-DCF lack a tracking module and rely on post-processing based on multi-frame association. Their feature extraction capabilities are also relatively weak, so they are not superior to the model detection devices proposed in the research. In addition, when DL-SORT, SSD, CSR-DCF, YOLOv4-tiny, FC-YOLO and FPN were tested in VOC data set, the average image processing response time was 15 ms, 20 ms, 35 ms, 32 ms, 19 ms and 37 ms, respectively. The research algorithm has the fastest processing time. This is due to the excellent dynamic parallel computing capability of DL-SORT hybrid algorithm for target detection and tracking. Although the DL-SORT algorithm excels in target tracking, the hybrid model may underperform in highly dynamic scenes, such as car racing or drone-captured football matches captured by drones. When DL and SORT are processed jointly in this model, the frame rate will be affected by the high-speed target, and the computation extension will gradually increase.

6 Conclusion

To address the precision issues in component detection, this study developed a DL-SORT-based hybrid model for automatic recognition and grasping of electronic components. In the construction of the model, an improved visual feature recognition method, combining recursive labeling and BRIEF, was used to optimize image acquisition and enhance the target recognition capability of the electronic component model. Experimental results showed that the DL-SORT hybrid algorithm achieved a recognition accuracy of 92.6% for human detection, while the SSD, CSR-DCF, and YOLOv4-tiny target detection algorithms had recognition accuracies of 90.0%, 78.2%, and 84.5%, respectively, all of which were lower than the proposed algorithm. Furthermore, empirical analysis of the constructed electronic component automatic recognition and grasping hybrid model revealed an MAE of 2.12 when the target count reached 70, meeting the accuracy requirements for electronic device grasping. While models constructed using SSD, CSR-DCF, and YOLOv4-tiny target detection algorithms had MAE values of 3.12, 2.82, and 3.01, respectively, all of which were higher than that of DL-SORT. In conclusion, the electronic component automatic recognition and grasping hybrid model based on the DL-SORT multi-target visual detection algorithm enhances the intelligent recognition capability of electronic components and significantly improves production efficiency. However, the current experiments still have limitations, such as computational resource consumption and data recognition constraints. Therefore, future work could expand the target recognition range and enhance the experimental validity.

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Predicting California Bearing Ratio Using Hybrid Least Square Support Vector Regression with IAOA, ESMA, and RKO Meta-Heuristic Algorithms

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The California Bearing Ratio (CBR) test is a crucial geotechnical parameter for evaluating soil strength. This study proposes a Least Squares Support Vector Regression (LSSVR) model to predict CBR values using compaction characteristics, moisture content, and soil properties. A dataset comprising 110 soil samples was used, with 70% for training and 30% for testing. To enhance predictive accuracy, three meta-heuristic algorithms—Improved Arithmetic Optimization Algorithm (IAOA), Equilibrium Slime Mould Algorithm (ESMA), and Runge Kutta Optimization (RKO)—were integrated with LSSVR, forming hybrid models LSIA, LSEM, and LSRK. These algorithms optimized the regularization parameter (C) and kernel parameter (Gamma) to improve model generalization. Performance evaluation using R^2, RMSE, and MAE showed that the LSIA model outperformed all others, achieving an R^2 of 0.9975 (training) and 0.9932 (testing), along with the lowest RMSE (0.5489) and MAE (0.3176). The results confirm that LSIA exhibits superior predictive accuracy and robustness, making it a reliable and time-efficient alternative for geotechnical applications.

Povzetek: Predstavljen je hibridni model LSIA, ki s pomočjo metahevristike IAOA optimizira LSSVR in dosega kvalitetno napovedovanje indeksa nosilnosti (CBR) tal v geotehniki.

1 Introduction

The California Bearing Ratio (CBR) is a widely used parameter in engineering to evaluate the mechanical properties of soil subgrade, which are crucial for designing flexible pavements. Assessing the CBR value is vital for determining the suitable thickness of the roadway layer that can handle the expected traffic volume [1]–[3].

In particular, when the CBR value rises, increasing the pavement layer's thickness is essential to provide enough resistance against the anticipated load. By empowering engineers to make informed decisions on the use of materials, structural design, and building techniques, researchers help build structures that are long-lasting, sustainable, and CBR. A 50 mm diameter circular plunger is used to pierce a soil mass; the pressure per unit area needed is measured and separated by the comparable diffusion in a reference material at a continuous rate of 1.25 mm each minute. This metric is known as the CBR. A ratio of 2.5 to 5 mm is usually used to evaluate penetrations; greater results are obtained with the 5 mm ratio than with the 2 mm ratio [4], [5]. Compacted samples that have been undisturbed or reconstituted can be used in laboratory studies in either a saturated or unsaturated water environment. It is important to remember that current studies have shown that the condition of the material during testing can have a big impact on the CBR values [6]–[8]. CBR is a fundamental parameter in geotechnical engineering used to assess soil strength. Using a standard plunger, the CBR value is obtained by measuring the pressure obligatory to penetrate a soil sample. The main ingredients of CBR include the soil type, moisture content, and compaction level. These factors significantly impact the CBR value and are crucial in accurately predicting soil strength. Understanding the ingredients of CBR is essential in designing and constructing reliable and robust structures that can withstand various loads and conditions [9], [10].

The OMC represents the moisture content at which the soil is most compact and has the greatest strength. In the CBR test, the optimum moisture content (OMC) is the moisture content at which the soil sample has the highest CBR value. Several CBR tests are applied on soil samples with varying moisture contents to determine the OMC. The CBR value is measured for each moisture content, and the results are plotted on a graph with the CBR value on the $y-axis$ and moisture content on the $x-axis$. The moisture content at which the CBR value is the highest is the OMC [7]. The OMC is an important parameter in designing and constructing roads, pavements, and other infrastructure. If the soil is too dry, it may be hard and brittle, leading to cracking and other damage. If the soil is wet, it may be too soft and weak, leading to deformation and failure under load. Therefore, it is important to determine the OMC to ensure that the soil has the required strength and stability for the intended use [11].

However, when done in a laboratory setting, calculating the CBR value may be difficult and costly. As a result, researchers have explored alternative methods, such as utilizing machine learning (ML) models, to predict the CBR value of soil subgrades. ML, a subfield of artificial intelligence [12], focuses on creating algorithms that have the capacity to learn from data and become more effective over time. This study area has clear benefits for effectively handling sizable and intricate information, making it possible to spot underlying patterns and produce accurate forecasts. Several approaches have been thoroughly examined in ML, such as reinforcement learning, supervised learning, deep learning, unverified learning, and others. ML applications may be found in a wide range of industries, including manufacturing, transportation, finance, and engineering [13]–[17].

Table 1 presents the summary of some previous studies related to CBR prediction.

Table 1: Summary of previous studies related to CBR prediction.

Article	Model	Evaluator	
		R^2	RMSE
[18]	MLR	0.841	-
[19]	ANN	0.981	1.187
[20]	ANN	0.945	2.81
[21]	GPR	0.999	0.139
[22]	ANN	0.970	1.691
[23]	MARS-L	0.969	0.036
[24]	RF	0.98	1.43
[25]	LGBM	0.947	0.33

In this research, ML methodologies are employed to address complex systems and analyze multiple variables to estimate the CBR measure. The study assumes a methodological method centered around utilizing the LSSVR technique. Accurate forecast models for CBR are of utmost importance. However, optimizing the parameters of LSSVR is crucial to enhance its predictive performance. To tackle this issue, the paper explores the integration of three meta-heuristic algorithms: the Improved Arithmetic optimization algorithm ($IAOA$), the Equilibrium Slime Mould Algorithm (ESMA), and Runge Kutta Optimization (RKO). By streamlining the CBR −related design and construction procedures, this study emphasizes the positive impact that can have on the substructure sector and the built situation. To evaluate the proposed framework, the study collects a dataset of CBR and conducts comparative analyses to assess the effectiveness of this approach compared to traditional optimization methods.

The choice of IAOA, ESMA, and RKO for optimizing LSSVR in CBR prediction was guided by their unique computational advantages in balancing exploration and exploitation, ensuring efficient hyperparameter tuning. IAOA enhances global search capability while mitigating premature convergence, making it ideal for optimizing non-linear geotechnical data. Inspired by slime mould foraging behaviour, ESMA introduces an equilibrium-based update mechanism that improves search diversity and robustness. RKO, rooted in the Runge-Kutta numerical method, provides a structured and stable optimization process, ensuring precise parameter tuning.

2 Materials and methodology

2.1 Data gathering

As shown in Table 2, the experimental samples comprising the CBR dataset were split into two sets: a training phase comprising 76 samples (70%) and a test phase comprising 33 samples (30%). Based on these predictor factors, an $LSSVR$ model was used to predict the CBR. The dataset utilized in this investigation came from an investigation carried out by Ikeagwuani [26]. It uses a combination ratio obtained using the response surface and Taguchi array experimental techniques. The stabilizers and modified extensive soil qualities shown in Table 2 are linked to the output variable, CBR value, and have inherent geotechnical characteristics. Compaction traits and atterberg limits, such as liquid limit (LL), plasticity index (PI), plastic limit (PL), OMC, and maximum dry density (MDD), are among the physical features of the changed soil. The input variables are the stabilizers, namely SDA, OPC, and QD.

Table 2: The statistical properties of model input and target values.

Indicator	Statistical Properties								
	LL	PL	PI	MDD	OMC	SDA	QD	OPC	CBR
Max	52.1	37.2	19.5	1.777	29.5	20	20	8	66.75
Min	21.2	17.9	2.1	1.365	18.9	0	0	2	19.69
Avg	35.85	26.68	9.162	1.493	24.14	10.66	10.64	4.945	39.959
St. Dev.	6.154	4.281	4.115	0.088	2.427	7.155	8.196	2.380	10.866

2.2 Least square support vector regression (LSSVR)

As a development to SVR that can handle issues with function estimation, regression, and classification, Vandewalle and Suykens introduced $LSSVR$ [27]. Their articles contained documentation of this. SVR was developed as a supervised ML approach in 1995 by Vapnik and his coworkers. However, since LSSVR employs linear equations rather than quadratic ones, which simplifies the optimization process, it has an advantage over SVR [28]–[31]. The $LSSVR$ process, showed in Fig. 1, includes utilizing the input x_i and the output y_i time series to direct the $LSSVR$ function as presented below.

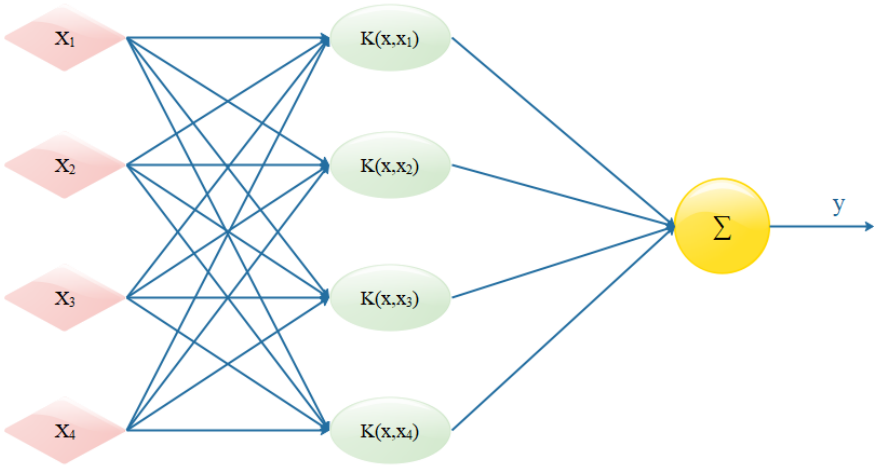


Figure 1: The $LSSVR$ model is used to forecast wind power and speed.

$$y(x) = \varpi^M \psi(x) + d \tag{1}$$

In Eq. (1), x can assumed that an input and the output (y) is resolute by the weight vector (ϖ), which has min extents, the partiality term d and the charting term ψ [32]. The following may be used to exemplify the cost function for $LSSVR$:

$$minJ(\varpi, a) = \frac{1}{2}\varpi^M \varpi + \frac{\tau}{2}\sum_{i=1}^{N} a_i^2 \tag{2}$$

which is limited by the following:

$$y_i = \varpi^M \psi(x_i) + d + a_i, \quad (i = 1,2,3, \dots, N) \tag{3}$$

For a given input x_i, the values of the training error and the regularization constant are provided by a_i and τ, respectively. The Lagrange multiplier (LM) optimum programming technique is used for solving Eq. (2). The constraint problem needs to be changed into a non-constraint problem to use this method to derive the objective function [33], [34]. The Lagrange function (L) can be intended in the following:

$$L(\varpi, d, a, \delta) = J(\varpi, a) - \sum_{i=1}^{N} \delta_i \{\varpi^M \psi(x_i) + d + a_i - y_i\} \tag{4}$$

Here δ_i is the LM.

$Karush - Cohen - Tucker$ [35], using the partial derivative calculations of Eq. (4) about $\omega, b, e,$ and β independently, as found:

$$\begin{cases} \varpi = \sum_{i=1}^{N} \delta_i \psi(x_i) + d \\ \sum_{i=1}^{N} \delta_i = 0 \\ \delta_i = \tau^{ai} \\ \varpi^M \psi(x_i) + d + a_i - y_i = 0 \end{cases} \tag{5}$$

It is possible to derive the linear equations by removing the variables from a_i and ϖ can be stated as:

$$\begin{pmatrix} 0 & -G^M \\ G & \Omega + \tau^{-1} G \end{pmatrix} \begin{pmatrix} d \\ \beta \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \tag{6}$$

Here $G = (y_1, \dots, y_N), \Omega = (\psi(x_1)^M y_1, \dots, \psi(x_N)^M y_N, P = (1, \dots, 1), \beta = (\beta_1, \dots, \beta_1)$.

Under $Mercer's$ standard (to get more explanations of $Mercer's$ standard, refer to [36]), it can be mentioned that the kernel is articulated as $s(x, x_i) = f(x)^M f(x_i), i = 1,2,3, \dots, H$. Consequently, the $LSSVR$ can be formulated as follows:

$$f(x) = \sum_{i=1}^{N} \delta_i s(x, x_i) + d. \tag{7}$$

$$s(x, x_i) = exp\left(-\frac{\|x - x_i\|^2}{2\varrho^2}\right). \tag{8}$$

2.3 Equilibrium slime mould algorithm (ESMA)

Slime mold's (SM) foraging habits offer a potential basis of inspiration to create successful and efficient optimization techniques [37]. The ESMA algorithm begins by initializing each slime mold's position using a randomization procedure, ensuring a diverse search space exploration. This is mathematically represented by Eq. (9). However, beyond initialization, ESMA primarily mimics the dynamic foraging behavior of slime molds, where individuals adjust their positions based on the concentration of nutrients in their surroundings. This bio-inspired movement strategy allows the algorithm to balance exploration and exploitation, enhancing optimization efficiency.

$$\vec{X_i}(t = 1) = r_1.(UB - LB) + LB, \quad i = 1,2, \dots, N. \tag{9}$$

Here, UB and LB indicate the upper and lower bound. The aligning model for the $i - th\ SM$, indicated as X_i $(j = 1,2, \dots, N)$, in the ensuing iteration $(t + 1)$, is recognized using SMA as follows:

$$\vec{\mathrm{X}}_i(t+1)=\begin{cases} r_1.(UB-LB)+LB, & r_1<z \\ \vec{\mathrm{X}}_{Gbest}+\overrightarrow{step}_a.\left(\vec{\mathrm{U}}.\vec{\mathrm{X}}_C-\vec{\mathrm{X}}_D\right), & r_2<P_i\ (t)\ \ and\ r_1\geq z \\ \overrightarrow{step}_b\ .\ \vec{\mathrm{X}}_i(t), & r_2\geq P_i\ (t)\ \ and\ r_1\geq z \end{cases} \tag{10}$$

The $\vec{\mathrm{X}}_{Gbest}$ represents the global best fitness value attained throughout iterations one through t. Moreover, the variables r_1 and r_2 resemble to change values within the choice of $[0,1]$.

To eliminate and distribute the SM, a chance signified by z is used. Inside the background of this paper, z is a continuous worth of 0.03 [38]. Eq. (11) is applied to type the suitability values in climbing instruction.

$$[sortf, sortIndex]=sort(f),\ \ where\ f=\{f_1,f_2,\ldots..,f_N\} \tag{11}$$

In Eq. (11) sorts the elements of $f=\{f1,f2,\ldots,fN\}$ in ascending order, producing $sortf$, the sorted version of f. The corresponding indices of the original elements are stored in $sortIndex$. Here, $sort()$ denotes the sorting operation, which arranges elements in increasing order unless otherwise specified.

Eq. (12) is working to calculate $\vec{\mathrm{U}}$.

$$\vec{\mathrm{U}}(sortIndex(j))=\begin{cases} 1+r_3.\log\left(\frac{f_{Lbest}-sortf\ (j)}{f_{Lbest}-f_{Lworst}}+1\right) & 1\leq j\leq \frac{N}{2} \\ 1-r_3.\log\left(\frac{f_{Lbest}-sortf\ (j)}{f_{Lbest}-f_{Lworst}}+1\right) & \frac{N}{2}<j\leq N \end{cases} \tag{12}$$

Eq. (12) calculates $\vec{\mathrm{U}}$, which represents (explain its purpose, e.g., an updated search variable). The equation follows a piecewise definition, where for $j\leq 2$, [explain the significance], and for $j>2$, [explain the significance]. A random number, r_3 is equally dispersed over the [0,1] range. The values obtained for the resident worst and greatest fitness for the present iteration are indicated by f_{Lworst} and f_{Lbest}, correspondingly. Eqs. (13-14) are working to compute these fitness values.

$$f_{Lbest}=sortf(1) \tag{13}$$

$$f_{Lworst}=sortf(N) \tag{14}$$

Eqs. (13) and (14) utilize f_{Lworst} and f_{Lbest}, which represent the worst and best fitness values within the current iteration. These values are obtained by (explain the method, sorting the fitness values from Eq. (11)). To maintain consistency with Eq. (12), we define these as (choose a single consistent term, 'present iteration worst and best fitness values') throughout the text. Under is the formulation that describes the inconstant P_i, which signifies the likelihood of picking the course of $i-th\ SM$:

$$P_i=\tanh|f(X_i)-f_{Gbest}| \tag{15}$$

Eq. (15) defines $P_i=\tanh|f(X_i)-f_{Gbest}|$, where f_{Gbest} represents the best fitness value obtained from the first iteration up to the current iteration. This ensures that P_i reflects the difference between the current solution's fitness and the globally best fitness found so far. For apiece $i=1,2,\ldots,N$, the suitability rate of the $i-th\ SM$ in X_i is resolute by $f(X_i)$. The greatness of the $step\ size$ is designated by $\overrightarrow{step}_a$ and is strongminded by an unchanging delivery rang since $-a$ to a. Also, the size of the step, signified by $\overrightarrow{step}_b$, is resolute by an unchanging delivery rang since $-b$ to b. The morals of a and b are strongminded by Eq. (16); this is determined by the max iteration T and the current iteration T:

$$a=\operatorname{arctanh}\ \left(-\left(\frac{t}{T}\right)+1\right) \tag{16}$$

$$b=1-\frac{t}{T} \tag{17}$$

Eq. (10) shows that even with the $SMA's$ encouraging findings, the search procedure still has to be improved. It is important to recollect that count arbitrary SM can variation the exploration's direction. Local least may restrict the efficacy of the search strategy when choosing individuals to seek for $\vec{X}_D$ and $\vec{X}_C$ from a N slime molds' sample. This part presents the $EOSM$, a novel optimization method. By using an equipoise pool of four bigger location courses, this approach replaces the location vector $\vec{X}_A$. The EO idea is then applied to determine this selection's average position. Eq. (18) provides an exact definition of the equilibrium pool's constituents.

$$\begin{aligned} \vec{X}_{eq(1)}&=X\left(sortIndex(1)\right)\\ \vec{X}_{eq(2)}&=X\left(sortIndex(2)\right)\\ \vec{X}_{eq(3)}&=X\left(sortIndex(3)\right)\\ \vec{X}_{eq(4)}&=X\left(sortIndex(4)\right)\\ \vec{X}_{ave}&=\frac{\vec{X}_{eq(1)}+\vec{X}_{eq(2)}+\vec{X}_{eq(3)}+\vec{X}_{eq(4)}}{4} \end{aligned} \tag{18}$$

The equilibrium pool is built using a collection of five-position vectors, denoted by $\vec{X}_{eq,pool}$.

$$\vec{X}_{eq,pool}=\{\vec{X}_{eq(1)},\vec{X}_{eq(2)},\vec{X}_{eq(3)},\vec{X}_{eq(4)},\vec{X}_{ave}\} \tag{19}$$

In $ESMA$, the place vector for the $i-th\ SM$, X_i $(j=1,2,\ldots,N)$, throughout the original iteration $(t+1)$ is signified by the subsequent equation:

$$\vec{X}_i(t+1)=r_1.(UB-LB)+LB, when\ r_1<z \tag{20}$$

$$\vec{X}_i(t+1)=\vec{X}_{Gbest}+\overrightarrow{step}_a.\left(\vec{U}.\vec{X}_{eq}-\vec{X}_D\right),when\ r_2<p_i(t)\ and\ r_1\geq z \tag{21}$$

$$\vec{X}_i(t+1)=\overrightarrow{step}_b\ .\ \vec{X}_i(t)\ ,\ when\ r_2\geq p_i(t)\ and\ \ r_1\geq z \tag{22}$$

The location vector $\vec{X}_{eq}$ is learned by picking a vector at random from the evenness pool. The algorithmic tool z guarantees the success of $ESMA$ by encouraging exploration throughout the search phase by restricting restricted local occurrence. This is accomplished using a

threshold value of 0.03 that was determined through testing. It is important to remember that the ESMA method combines the local best position from the best-so-far equilibrium pool, the global best position, and a random vector for modifying the position vector in the subsequent iteration. This approach allows for a fair trade-off between exploration and exploitation. The recommended $ESMA$ is fully described in Algorithm 2.

Algorithm 2: $ESMA$ Algorithms pseudo-code

Begin
Inputs: $N, D, T, UB, LB, and\ z.$
Initialization: $x_i = \{x_i^1, x_i^2, \dots, x_i^D\}\ for\ i = 1, 2, \dots, N\ at\ a\ random\ position\ within\ the\ search\ boundary\ [LB, UB] for\ a\ D\ dimension\ at\ initial\ iteration\ t = 1\ to\ form\ X = [\vec{X}_1, \vec{X}_2, \dots, \vec{X}_i, \dots, \vec{X}_N]'.$
While $(t \le T)$
→ $Evaluate\ the\ fitness\ f(x)\ of\ N\ slime\ mould.$
→ $Sort\ the\ fitness\ value\ in\ ascending\ order\ (for\ minimization\ problem)\ using\ Eq.(17) and\ determine\ the\ f_{Lbest}\ using\ Eq.(19), f_{Lworst}\ using\ Eq.(20) and\ constructing\ the\ \vec{X}_{eq,pool}\ using\ Eq.(18).$
→ $Determine\ the\ weighting\ factor\ \vec{U}\ using\ Eq.(18).$
→ $Update\ the\ \vec{X}_{Gbest}.$
→ $Determine\ the\ a\ and\ b.$
For $i = 1 : number\ of\ slime\ mould\ (N)$
→ $Generate\ a\ random\ value\ r_1.$
If $r_1 < z$
$Update\ the\ position\ vector\ \vec{X}_i(t+1) = r_1.(UB - LB) + LB.$
Else If $r_1 \ge z$
$Update\ the\ probability\ p_i, \overrightarrow{step}_a\ and\ \overrightarrow{step}_b.$
$Randomly\ choose\ one\ position\ vector\ \vec{X}_{eq}\ from\ the\ equilibrium\ pool.$
$Generate\ a\ random\ value\ r_2.$
If $r_2 < p_i$
$Select\ a\ random\ position\ \vec{X}_D\ a\ vector\ from\ X.$
$Update\ the\ position\ vector\ \vec{X}_i(t+1) = \vec{X}_{Gbest} + \overrightarrow{step}_a.(\vec{U}.\vec{X}_{eq} - \vec{X}_D).$
Else If $r_2 \ge p_i$
$Update\ the\ position\ vector\ \vec{X}_i(t+1) = \overrightarrow{step}_b.\vec{X}_i(t).$
End If
End If
End For
→ $t = t + 1$
End while
Output: $\vec{X}_{Gbest}$
End

2.4 Runge Kutta optimization (RUN)

$$Z_{ij} = LB_j + r_1 \times (UB_j - LB_j)$$
$$i = 1, 2, \dots, N \quad , \quad j = 1, 2, \dots, P \tag{23}$$

The RKM, which was used to calculate solutions for first-order gap equations, is the foundation of the RUN optimization algorithm [39], [40]. The Runge Kutta method (RKM) generally yields a precise numerical result based on functions alone, without the need for any gradient information. Calculating slope within the RKM framework is crucial to the functioning of the RUN optimization algorithm to simulate the exploration abilities of swarm-based optimization as it enables the algorithm. The following are the phases that make up the mathematical equation of the RUN algorithm:

- According to the bounds of the search space (LB, UB), the first solutions for N agents are created during the startup step. To do this, the following equation is used:

The problem's dimension is factored into the formula and is represented by P, LB_j and UB_j represent the jth variable's $lower$ and $upper$ bounds in the solution set Z_{ij}, here i ranges from 1 to N, on behalf of the complete number of exploration agents. r_1, r_2, and r_3 are step coefficients used to control the magnitude of the function evaluations in each iteration.

- In order to update solutions, the RUN algorithm uses a search mechanism (SM) that makes use of the RKM to change the location of the current solution on each iteration. The expression for this mechanism is:

$$Z_i = \begin{cases} Z_{CF} + S_{FM} + \mu \times randn \times Z_{mc} \ , if\ rand \le 0.5 \\ Z_{mF} + S_{FM} + \mu \times randn \times Z_{ra} \ , \ otherwise \end{cases} \quad (24)$$

In Eq. (24), $Z_{CF} = (Z_c + r \times SF \times g \times Z_c)$ and $S_{FM} = SF \times SM$. $Z_{ra} = (Z_{r1} - Z_{r2})$, $Z_{MF} = (Z_M + r \times SF \times g \times Z_m)$ and $Z_{MC} = (Z_m - Z_c)$. The direction of the search is changed by using the integer number r, which is between -1 and 1. Conversely, the random numbers represented by the symbols μ and g range from 0 to 1, respectively, and 0 to 2. The following details apply to the adaptable factor SF:

$$SF = 2 \times (0.5 - rand) \times f$$
$$f = a \times \exp\left(-b \times rand \times \left(\frac{t}{tmax}\right)\right) \quad (25)$$

t tracks the current iteration in the optimization process. $Tmax$ is a symbol for the total number of iterations. In Eq. (26), the Z_c and Z_m values employed are distinct as:

$$Z_c = \varphi \times Z_i + (1 - \varphi) \times Z_{r1} \quad (26)$$

$$Z_m = \varphi \times Z_b + (1 - \varphi) \times Z_{pb} \quad (27)$$

Z_c and Z_m are weighting parameters that modulate the contribution of each function evaluation in the iterative process. A randomly generated number between 0 and 1, denoted by the φ, is included in Eq. (26 and 27). Here, Z_b and Z_{pb} indicate the top agent at each iteration and the top agent thus far, correspondingly. In Eq. (24), the SM is rationalized employing the subsequent equation:

$$\begin{aligned} &\mathrm{SM} = \frac{1}{6}(Z_{RK})\Delta Z; \\ &Z_{RK} = k_1 + 2 \times k_2 + 2 \times k_3 + k_4 \\ &k_1 = \frac{1}{2\Delta Z}(rand \times Z_w - u \times Z_b) \\ &k_2 = \frac{1}{2\Delta Z}(rand \times (Z_w + rand_1 \times k_1 \times \Delta Z) \\ &\qquad - UZ \\ &k_3 = \frac{1}{2\Delta Z}\Big(rand \times (Z_w \\ &\qquad + rand_1 \times (\frac{1}{2}k_2) \times \Delta Z\Big) \\ &\qquad - UZ_b \end{aligned} \quad (28)$$

$$\begin{aligned} k_4 &= \frac{1}{2\Delta Z}(rand \times (Z_w + rand_1 \times k_3 \times \Delta Z) \\ &\qquad - UZ_{b2} \\ u &= round(1 + rand) \times (1 - rand) \\ UZ &= (U \times Z_b + rand_2 \times k_1 \times \Delta Z) \\ UZ_b &= \left(U \times Z_b + rand_2 \times (\frac{1}{2}k_2) \times \Delta Z\right) \\ UZ_{b2} &= (U \times Z_b + rand_2 \times k_3 \times \Delta Z) \end{aligned}$$

Eq. (28) formulates the update rule for Z_{RK}, which plays a role in the Selection Mechanism (SM) by determining candidate solutions. The parameters u, k_1, and k_2 influence this update process and are defined as follows:"

u: A randomly generated value between 0 and 1, used to introduce stochastic variation.

k_1, k_2: Control parameters that balance the influence of different solutions (or learning factors, if applicable).

The symbols $rand1$ and $rand2$ characterize random statistics. The ΔZ (ΔZ controls how solutions are modified in each iteration) value is calculated as follows:

$$\begin{aligned} \Delta Z &= 2 \times rand \times |Stp|; \\ Stp &= rand \times ((Z_b - rand \times Z_{avg}) + y) \\ y &= rand(Z_n - rand \times (u - l)) \times \exp(-4 \\ &\qquad \times \frac{t}{tmax}) \end{aligned} \quad (29)$$

Stp represents a step size. l is an iteration index and y represents random variables.

The morals of Z_w and Z_b are updated in accordance with the formulas below:

Algorithm 2. Update Rule for Zw and Zb.

```
if
f (Zi) < f (Zpb)
Zb = Zi
Zw = Zpb
else
Zb = Zpb
Zw = Zi
end
```

- A variety of operators are used in the Enhanced Solution Quality stage in order to increase the convergence amount and prevent local ideals. The goal is to improve the superiority of answers, and the following procedure helps to do this:

$$\begin{aligned} Z_{new2} &= \begin{cases} Z_{new1} + r \times \omega \times \left|\left(Z_{new1} - Z_{avg}\right) + randn\right| \ , if\ \omega < 1 \\ \left(Z_{new1} \times Z_{avg}\right) + r \times \omega \times Z_{na} \qquad otherwise \end{cases} \\ Z_{na} &= \left|\left(u \times Z_{new1} - Z_{avg}\right) + randn\right| \quad , \quad c = 5 \times rand \\ \omega &= rand(0,2).\exp\left(-c\left(\frac{t}{tmax}\right)\right), \quad Z_{avg} = \frac{Z_{r1} + Z_{r2} + Z_{r3}}{3} \end{aligned} \quad (30)$$

Z_{avg} represents the average position of the agents in the search space, indicating the mean of the agent positions. c is a constant that controls the influence of the random

$$Z_{new1} = \delta \times Z_{avg} + (1 - \delta) \times Z_b \quad (31)$$

perturbation in the algorithm, balancing exploration and exploitation during optimization. w is the inertia weight, which influences the velocity of the agents, helping to balance exploration and exploitation phases. The condition $if\ w < 1$ has also been clarified to explain its role in controlling the convergence behavior of the optimization process.

A chance amount between 0 and 1 and an integer Z_{new1} represents the updated solution after applying the influence of the average position of the agents (Z_{avg}) and the best agent's position (Z_b). Amount r, which might have values of 1, 0, or -1, are involved in the calculation in Eq. (31). According to [31], if the fitness value of Z_{new2}

is not better than the level of fitness of Z_i, then there's an additional chance to revise the worth of Z_i. This may be done by applying the following equation:

$$Z_{new3} = (Z_{new2} - r_1 \times Z_{new2}) + SF \times D_Z$$
$$D_Z = (r_2 \times Z_{RK} + (v \times Z_b - Z_{new2})) \quad (32)$$

There is a random value in this equation r_1, r_2, and r_3. The value of v (variable) is figured as twice the alteration of r_3 and 0.5, where r_3 is a accidental amount in the variety $[0, 1]$ [41].

2.5 Improved arithmetic optimization algorithm (IAOA)

The AOA algorithm apprises the population using the finest global answer, but if it reaches the best local solution, the population will stop improving. This can lead to premature convergence in certain cases [42]. Additionally, AOA does not fully utilize the diverse information contributed by individual members of the population, which can limit its exploratory capability. To address these limitations, this paper introduces the IAOA. IAOA enhances population diversity through a structured subpopulation mechanism, ensuring better exploration and exploitation. By dynamically adjusting the population's composition and incorporating adaptive strategies, IAOA prevents stagnation in local optima and improves convergence toward the global optimum.

2.5.1 Mechanism for population control

The important AOA exploits arithmetic operatives ($Multiplication$ (" × "), $Division$ (" ÷ "), $Subtraction$ (" − "), $and\ Addition$ (" + ")) to haphazardly investigate the area surrounding an ideal answer. Though, this technique can result in a reduction in population diversity. To mitigate this issue, it is necessary to categorize the population.

2.5.1.1 The Original subpopulation

Arrange the populace based on their suitability values and take the top num_best those as the initial subpopulation.

$$num_{best} = round\left(0.1Z + 0.5Z\left(1 - \frac{t}{T}\right)\right) \quad (33)$$

With Z standing for the amount of individuals and t (current iteration) and T (maximum iterations) for the present iteration and max iterations, alternatively, the mathematical model is in the following: Z individuals exchange information about each other to update their locations. The equation dynamically adjusts the number of individuals in the initial subpopulation (num_best) based on the iteration progress. As t increases, the term $0.5Z(1 - t/T)$ decreases, leading to a gradual reduction in the size of the best-performing subpopulation.

$$x_{best_i}(t+1) = x_{best_i}(t) + rand \times \left(best(x) - \frac{x_{best_i}(t) + x_{best_j}(t)}{2} \times \omega\right) \quad (34)$$

$$x_{best_j}(t+1) = x_{best_j}(t) + rand \times \left(best(x) - \frac{x_{best_i}(t) + x_{best_j}(t)}{2} \times \omega\right) \quad (35)$$

Eq. (34) introduces randomness to enhance exploration by perturbing the position of an individual x_{best_j} using a stochastic factor. This ensures diversity and prevents premature convergence. Eq. (35), on the other hand, applies an averaging mechanism to refine the positions of individuals based on mutual influence, promoting exploitation by stabilizing movement around the best-found solution.

The i_th separate location in the next iteration is signified by $x_{best_i}(t+1)$, and the same smears to $x_{best_j}(t+1)$. $best(x)$ symbolizes the worldwide optimal found by people following t iterations. x_{best_j} is selectively selected from the first group, ω signifies the rate of information gathering, which may range from 1 to 2.

2.5.1.2 The next subpopulation

Select num_middle those from the populace to form the next subpopulation.

$$num_middle = round(0.3 \times Z) \quad (36)$$

These individuals are situated between num_best and num_worst in the po Selectively selected from the first group, ω signifies the rate of information gathering, which may range from 1 to 2. After that, they adjust their position, and the revised model looks like this:

$$x_{mid_i}(t+1) = x_{mid_i}(t) + Levy \times (best(x) - x_{mid_j}) \quad (37)$$

The random selection of x_{mid_j} comes from the second group. $Levy$ is the $Levy$ distribution function [43], and $x_{mid_i}(t+1)$ indicates where the i_th discrete will be located in the subsequent iteration.

The location of the i_th discrete in the next iteration is signified by $x_{mid_i}(t+1)$. $Levy$ refers to the $Levy$ distribution function [35], and x_{mid_j} is randomly chosen from the second category.

2.5.1.3 The third subpopulation

To establish the final subpopulation, indicate the number of the population's worst members.

$$num_worst = Z - (num_best + num_middle) \quad (38)$$

The final group of people use the following equation to update their position:

$$x_{worst_i}(t+1) = x_{worst_i} + \left(\frac{t}{T} \times best(x) - x_{worst_j}\right) \quad (39)$$

After t iterations, $best(x)$ signifies the global optimum discovered through individuals, and the location of the i_th separate in the next iteration is signified by $x_{worst_i}(t+1)$. During the early stages of $IAOA$, more persons are in the first subpopulation to accelerate the

global optimum update. The operator crowding problem is resolved close to the optimum as the algorithm runs because fewer individuals are in the first subpopulation. Furthermore, the size of the third subpopulation rises, so averting the population from becoming stuck in local optima. Another subpopulation looks for more gifted places by using Levy flying for small-step upgrades. This approach can successfully address the limitations of outdated AOA and enhance its performance. Fig. 2 depicts the $IAOA$'s flowchart.

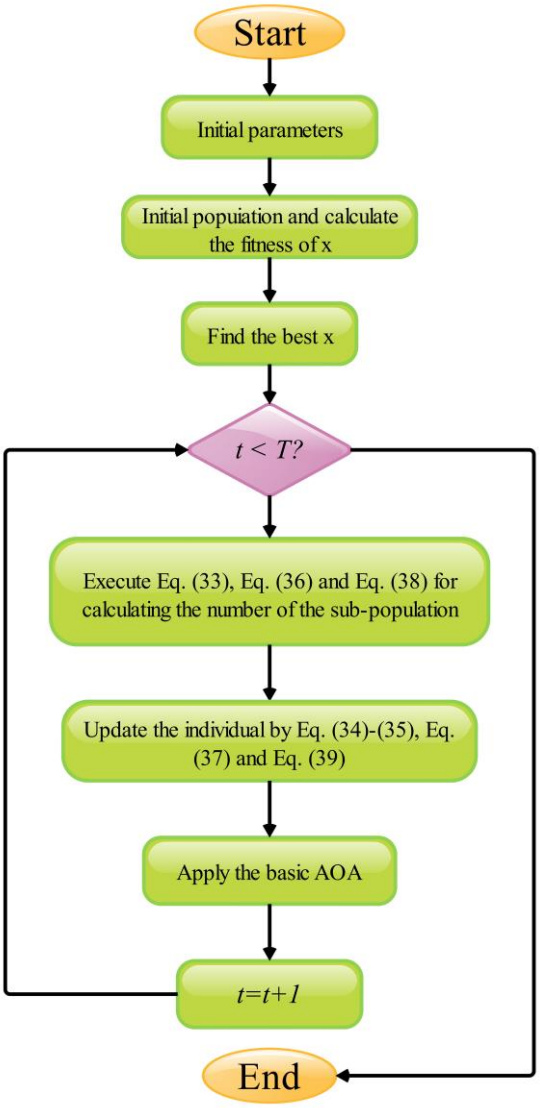


Figure 2: The flowchart of IAOA.

2.6 Performance evaluation methods

This study employed a set of evaluation metrics to assess the performance of the proposed models (LSIA, LSEM, and LSRK) for CBR prediction. Each of these metrics was selected to provide complementary insights into the models' predictive quality, accuracy, and robustness. Below is the justification for the selection of each evaluation metric:

1. **Symmetric Mean Absolute Percentage Error (SMAPE):**
   - **Justification:** SMAPE is a widely used metric in regression analysis, particularly in fields where data ranges vary significantly. Unlike traditional Mean Absolute Percentage Error (MAPE), SMAPE normalizes the error by both the actual and predicted values, making it scale-independent and preventing bias from high values in the dataset. It provides a balanced view of prediction error across different magnitudes of data, making it suitable for geotechnical engineering applications such as CBR prediction, where data variability is expected.
   - **Benefit:** SMAPE is particularly effective in capturing the relative error across the entire dataset and provides an intuitive percentage error that is easier to interpret regarding prediction accuracy.
2. **Root Mean Square Error (RMSE):**
   - **Justification:** RMSE is one of the most commonly used error metrics in regression problems, and it measures the square root of the average squared differences between predicted and actual values. RMSE is sensitive to large errors, giving more weight to large deviations between predicted and actual values, which makes it useful when large errors are particularly undesirable in the context of CBR prediction.
   - **Benefit:** RMSE is valuable for understanding the model's overall fit and is particularly useful when a high deviation from the actual values is considered critical. Its units are the same as the original data, which provides a tangible measure of model accuracy.
3. **Mean Absolute Error (MAE):**
   - **Justification:** MAE is another commonly used metric that measures the average absolute differences between predicted and actual values. Unlike RMSE, MAE does not square the errors and thus treats all errors equally without disproportionately penalizing larger deviations. This makes it a robust measure when understanding the average magnitude of prediction errors.
   - **Benefit:** MAE provides a more straightforward measure of the average error magnitude and is less sensitive to outliers than RMSE, making it a useful metric when a balanced view of prediction errors is needed.
4. **Coefficient of Determination (R^2):**
   - **Justification:** R^2, or the coefficient of determination, measures the proportion of variance in the dependent variable that is predictable from the independent variables. It is a key metric for understanding how well the

model fits the data. A higher R^2 value indicates that the model has a better fit and explains more of the variability in the data.

- **Benefit:** R^2 provides an overall indication of model performance, giving insight into how well the proposed models explain the variability in the CBR data. It is particularly useful for comparing the relative performance of different models.

5. **Scatter Index (SI):**

- **Justification:** SI is a metric used to evaluate the relative error by calculating the mean absolute error ratio to the actual data's mean value. It is useful for assessing how well the model captures the data's general trend while factoring in overestimating and underestimating predicted values.
- **Benefit:** The SI value provides an intuitive measure of the scatter of predicted values relative to the true values. This makes it particularly useful in applications like CBR prediction, where an accurate overall distribution of predictions is as important as fitting specific data points.

The evaluators comprise $SMAPE$, $RMSE$, MAE [44], R^2, SI. Below is a list of the formulae for each of these measurements. While lower values of metrics near to zero, including $RMSE, SMAPE, SI,$ and MAE, are preferable and a high R^2 value near to 1 shows the good performance of the algorithms.

$$R^2 = \left(\frac{\sum_{i=1}^{w}(p_i - \bar{p})(q_i - \bar{q})}{\sqrt{[\sum_{i=1}^{w}(p_i - p)^2][\sum_{i=1}^{w}(q_i - \bar{q})^2]}} \right)^2 \quad (40)$$

$$RMSE = \sqrt{\frac{1}{w}\sum_{i=1}^{w}(q_i - p_i)^2} \quad (41)$$

$$MAE = \frac{1}{w}\sum_{i=1}^{w}|q_i - p_i| \quad (42)$$

$$SMAPE = \frac{100}{w}\sum_{i}^{w}\frac{2 \times |q_i - p_i|}{|q_i| + |p_i|} \quad (43)$$

$$SI = \frac{RMSE}{meam(q_i)} \quad (44)$$

In this background, p_i and q_i define the forecast and experimental values, alternatively. The mean values of the experimental samples and predicted are defined by $\bar{p}$ and $\bar{q}$. Otherwise, w signifies the number of samples being measured.

2.7 Hyperparameter

Table 3 provides the optimized hyperparameters (C and Gamma) for the three hybrid models—LSIA, LSEM, and LSRK—demonstrating variations in parameter selection due to different optimization strategies. These hyperparameters were determined through random search, an efficient tuning method that explores a predefined range of values without requiring an exhaustive grid search. The regularization parameter (C) influences model complexity and error minimization trade-offs. Higher values, such as 382 in LSIA, suggest a model that prioritizes reducing training error, while lower values, such as 194 in LSRK, indicate a model with more flexibility to generalize to unseen data. Similarly, the Gamma parameter, which controls the influence of training samples in the RBF kernel, was highest in LSIA (2.123) and lowest in LSRK (1.193), signifying different levels of local adaptability in decision boundaries. The random search approach enabled an efficient and effective selection of hyperparameters, preventing the risk of overfitting while ensuring robust performance. Each optimization algorithm refined the chosen parameters, including IAOA for LSIA, ESMOA for LSEM, and RKO for LSRK. LSIA, which utilized the IAOA, exhibited the highest values for both C and Gamma, suggesting a more aggressive tuning strategy that improved model precision. LSEM and LSRK, optimized with the ESMOA and RKO methods, resulted in different parameter distributions, reflecting variations in their exploration-exploitation mechanisms.

Table 3: Hyperparameter of the developed hybrid models

Model	Hyperparameter	
	C	Gama
LSIA	382	2.123
LSEM	243	1.970
LSRK	194	1.193

2.8 Convergence

Fig. 3 shows the convergence of the developed hybrid models based on RMSE. The LSIA obtained the lower RMSE value compared to the other two models. The algorithms were initialized with a population size of 50, a maximum of 200 iterations, and a convergence threshold of RMSE. The experiments were conducted on a system, an Intel Core i7 processor, 64GB RAM, and an 11th Gen Intel(R), using Python 3.9 and Scikit-learn.

Beyond accuracy metrics, the computational efficiency of LSIA was assessed. The average training time for LSIA was 70 seconds, significantly lower than the LSRK and LSEM models, which required 4500 and 1500 seconds, respectively. Additionally, the LSIA model achieved convergence in fewer iterations (175 iterations), demonstrating its faster optimization process. While energy consumption was not explicitly measured, LSIA's reduced computational load suggests lower power usage, making it a feasible choice for large-scale geotechnical applications.

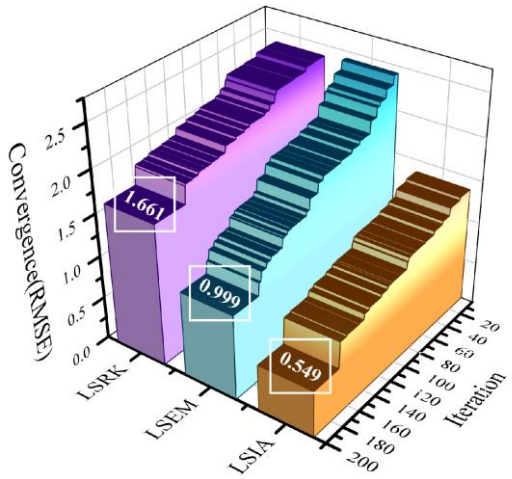


Figure 3: Convergence of the developed hybrid models.

2.9 Hybridization

The hybridization process in this study combines LSSVR with three optimization algorithms: IAOA, ESMA, and RKO. These algorithms fine-tune the LSSVR model's hyperparameters, enhancing its ability to predict the CBR. The hybridization process begins with initializing the LSSVR model and then applying each optimization algorithm to search for the optimal hyperparameters, such as C and gamma. The best-performing hyperparameters, derived through optimization, are then used to train the LSSVR model, ensuring improved prediction accuracy. Figs. 4 to 6 indicate the hybridization process for the LSIA, LSRK, and LSEM, respectively.

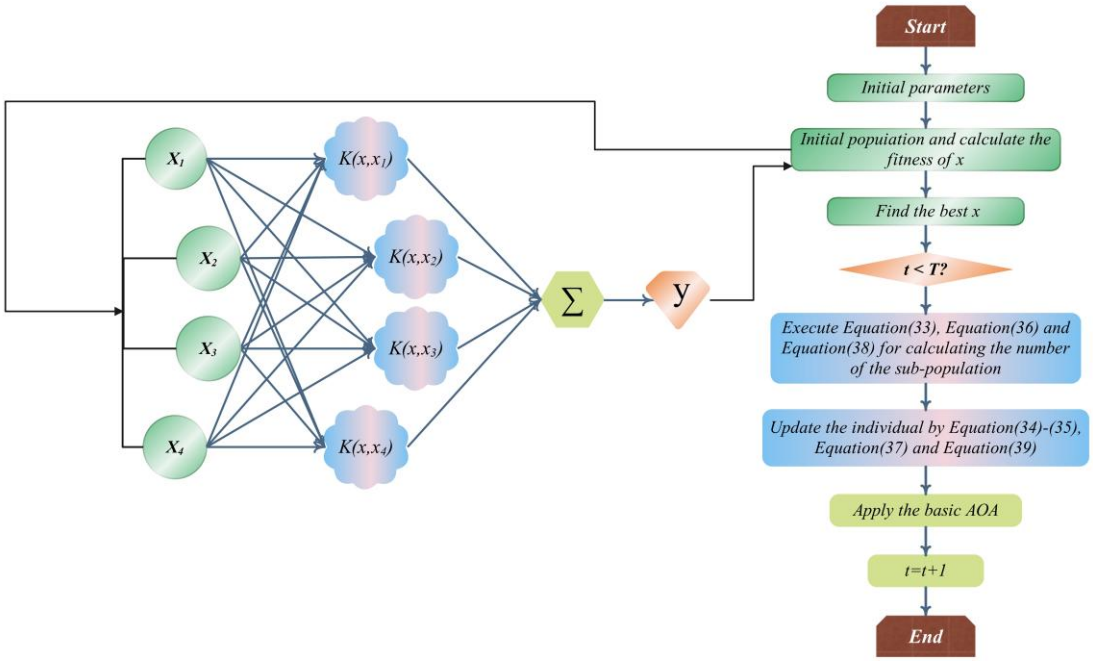


Figure 4: Hybridization of the LSSVR+IAOA.

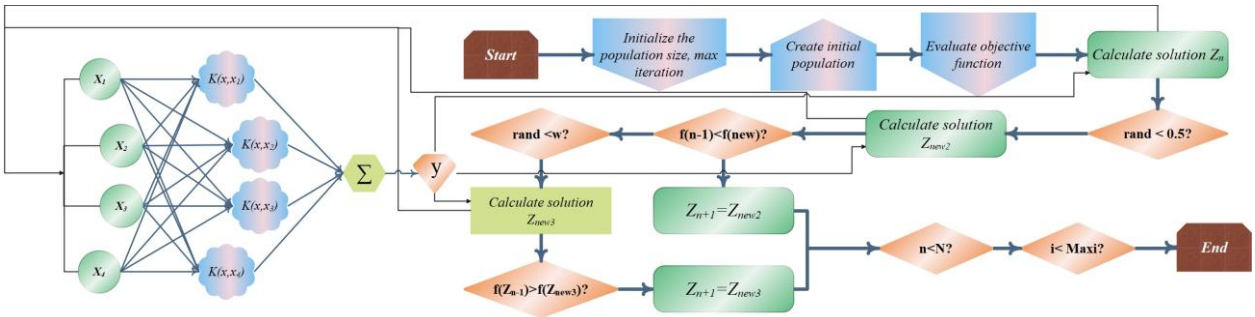


Figure 5: Hybridization of the LSSVR+RKO.

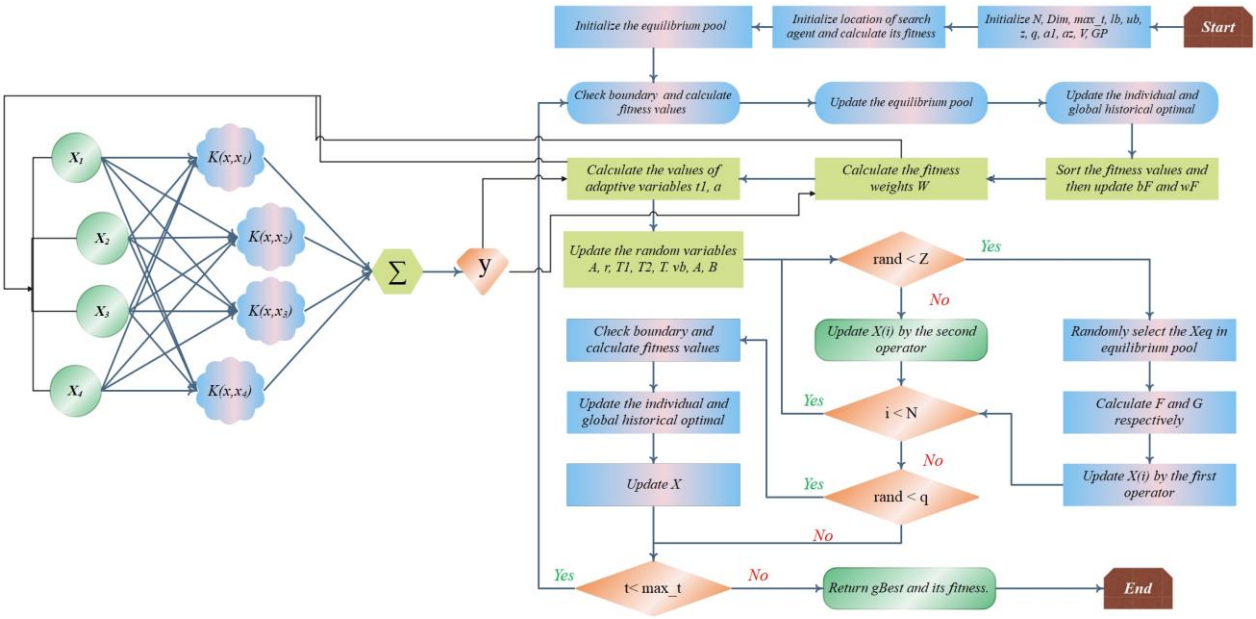


Figure 6: Hybridization of the LSSVR+ESMOA.

3 Results

Three models, namely LSIA, LSEM, and LSRK, were utilized in the research to forecast the CBR as output. The models were assessed based on their accuracy against experimental measurements during the training and testing stages. The experimental data were split into train (70%) and test (30%) sets to ensure an impartial evaluation of the models. The study utilized 5 statistical metrics containing R^2, $RMSE, SMAPE, SI$, and MAE to evaluate lengthily and comparison the research's algorithms. In the study, these evaluators were utilized to determine the efficacy of the algorithms secondhand.

Table 4 shows the results of the developed models. R^2 values, which indicate the percentage of the dependent variable's variation that the independent variable accounts for, were used to evaluate the models. The LSIA model indicated excellent predictive accuracy, with the highest R^2 values of 0.9975 and 0.9932 in the train and test stages. The LSEM model exhibited moderately high R^2 values of 0.9911 and 0.9828 in the train and test stages, while the LSRK model demonstrated lower R^2 values of 0.9756 and 0.9681 in the training and testing phases alternatively. However, all models demonstrated acceptable predictive accuracy.

The findings showed that the LSIA model had lower error indicators in the training and testing phases, indicating superior performance compared to the LSEM and LSRK models. Overall, the results suggest that LSIA may be a more suitable model for predicting CBR than LSEM and LSRK. However, when choosing a model for practical uses, additional aspects, including computational effectiveness, model complexity, and simplicity of implementation, should also be taken into account. Furthermore, the study revealed that all three optimization algorithms successfully enhanced the $LSSVR$ model's ability to forecast CBR, with the IAOA algorithm outperforming others by obtaining the highest R^2 values and the lowest $RMSE$ and MAE.

Table 4: Evaluation of developed hybrid models.

Hybrid Models	*Sections*	*Evaluators*				
		RMSE	R^2	*MAE*	*SI*	*SMAPE*
LSIA	Train	0.5489	0.9975	0.3617	0.014	0.0001
	Test	1.1270	0.9932	0.8324	0.0269	0.0006
LSEM	Train	0.9997	0.9911	0.8286	0.0255	0.0002
	Test	1.5589	0.9828	1.2039	0.0373	0.0008
LSRK	Train	1.6624	0.9756	1.3397	0.0425	0.0004
	Test	2.2305	0.9681	1.7882	0.0533	0.0013

The scatter plot in Fig. 7 illustrates a comparison of the hybrid models' performance according to two parameters: R^2 and RMSE. R^2 represents the level of agreement, while $RMSE$ represents the degree of dispersion. The plot's centerline is at the $X = Y$ coordinates, and the points' distance from the centre line reflects the model's accuracy level. The LSIA model demonstrated a high accuracy level, with its data points tightly clustered around the centerline, indicating a narrow range of dispersion. On the other hand, the data points of the LSEM and LSRK models showed comparatively equal performance levels.

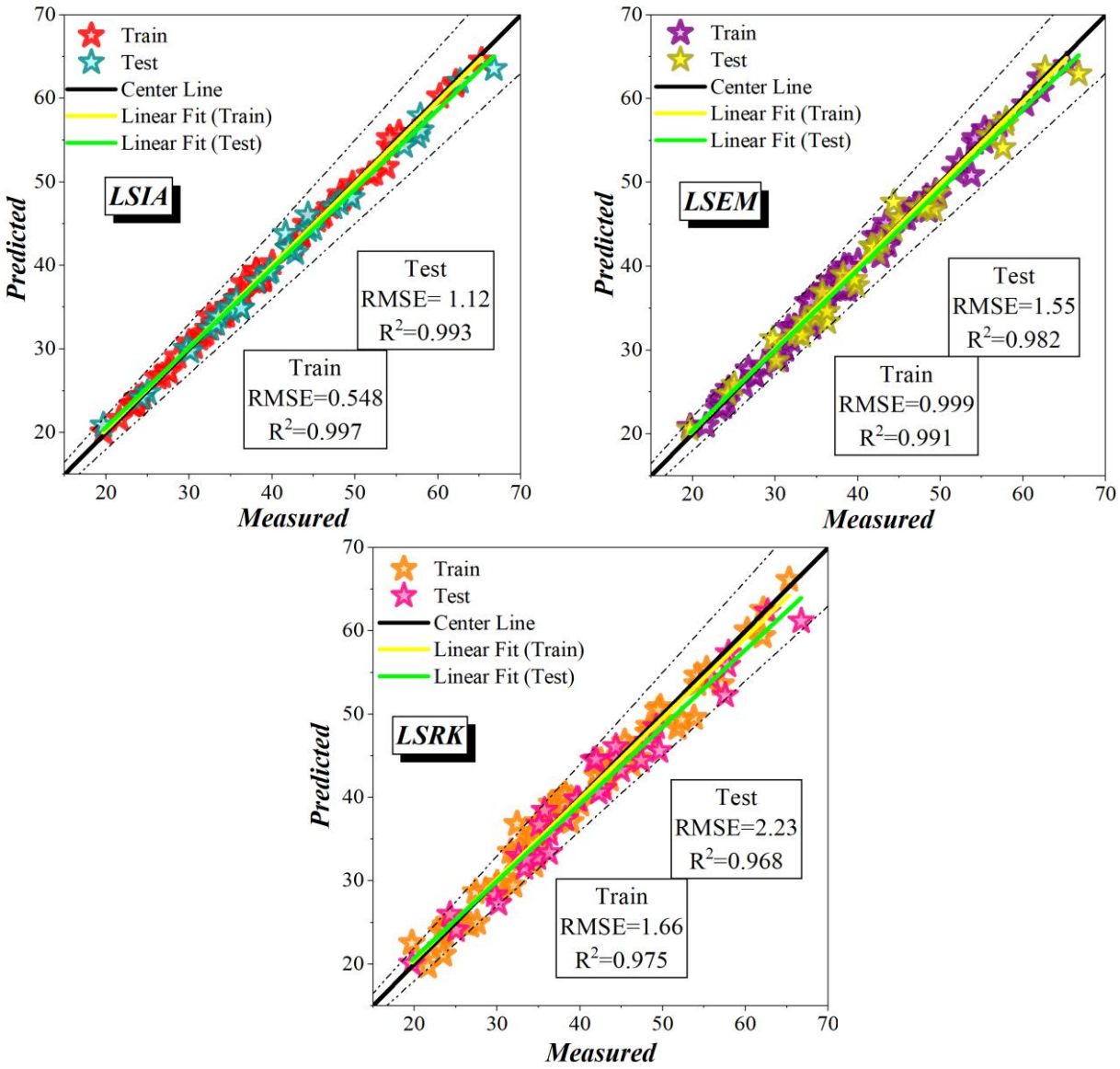
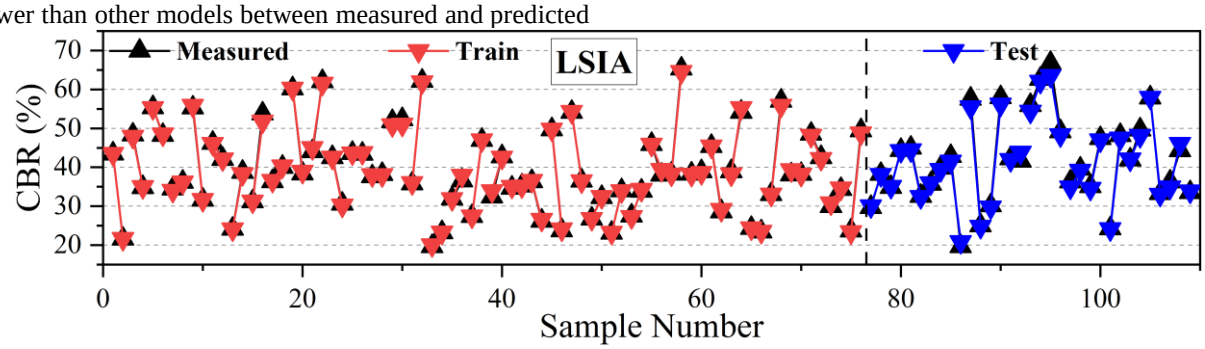


Figure 7: The models' scatter plot, which shows corresponding measured and predicted values

As shown in Fig. 8, the practical variance was influenced by the difference between the actual and estimated values, which decreased significantly in the testing phase. In the training phase, the LSIA model demonstrated minimal dispersion, and the difference was lower than other models between measured and predicted values. Although some samples showed disparities among actual and estimated values in the training phase, resulting in significant divergences, improvements in performance and positive learning outcomes have somewhat reduced this weakness.



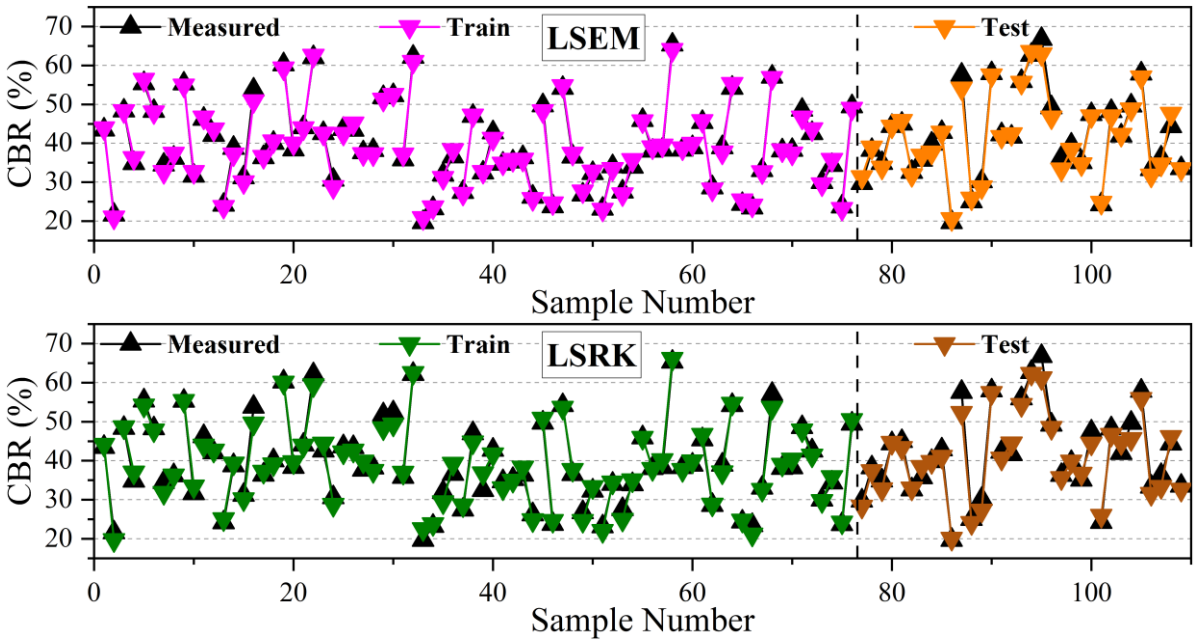


Figure 8: The comparison of the measured and predicted values

Figs. 9 and 610 visually present the error percentage in the models using a normal distribution plot and a violin diagram. In the LSIA model, the highest frequency of errors is below 1%, indicating high accuracy. In Fig. 10, most errors are below 5%, indicating good performance for LSIA. The performance of LSEM is comparable to that of LSIA when the error percentage in both figures is observed. In contrast, LSRK has the worst performance, with the most distributions in its data, as shown by the violin plot. These results suggest that LSIA is the most accurate and reliable model among the provided models.

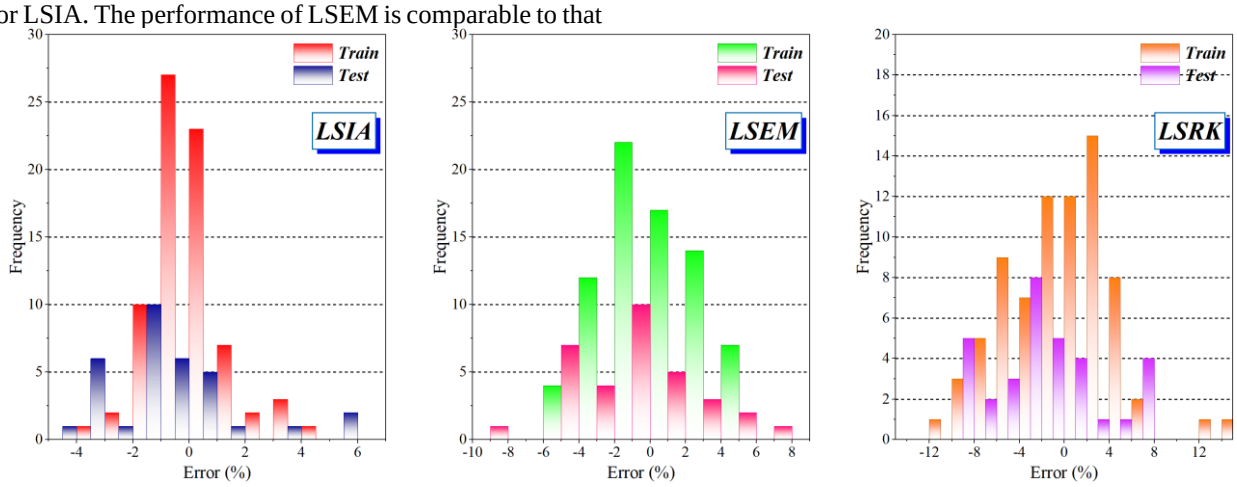


Figure 9: The error percentage of developed models is based on the line plot.

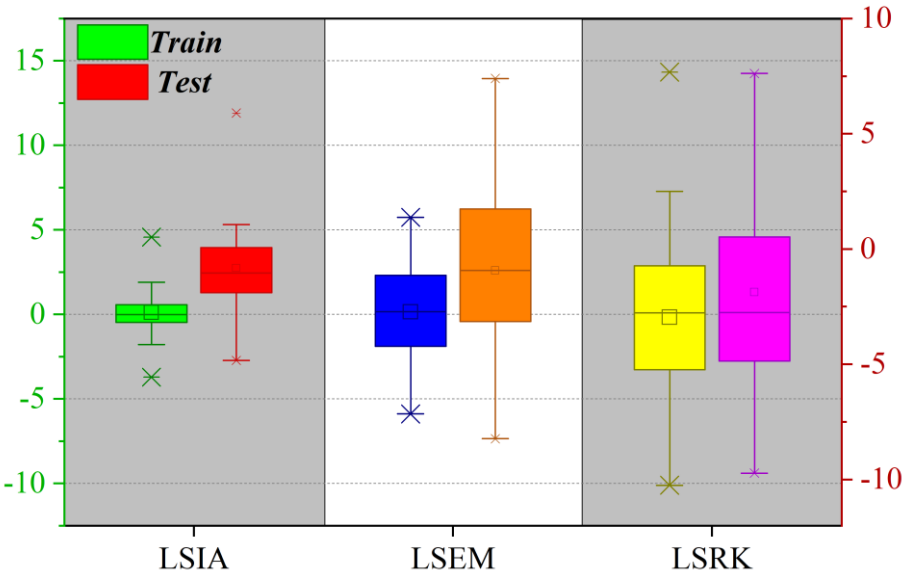


Figure 10: The violin diagram for error percentage of models.

4 Discussion

4.1 Comparison with other published studies

Table 5 presents a comparative analysis of previous studies on CBR prediction, showcasing different ML models along with their respective R^2 and RMSE values. The present study's LSIA model achieves an R^2 of 0.9932 and an RMSE of 1.1270, outperforming several state-of-the-art (STOA) models. Compared to traditional methods like MLR [19] with an R^2 of 0.841 and ANN [21,23] with R^2 values of 0.945 and 0.970, respectively, LSIA demonstrates significantly improved predictive accuracy. The RF model [25] (R^2 = 0.98) and LightGBM [26] (R^2 = 0.947) also fall short in comparison, indicating LSIA's stronger generalization ability.

Among the highest-performing SOTA models, GPR [22] achieves an R^2 of 0.999 and a remarkably low RMSE of 0.139, while MARS-L [24] attains an R^2 of 0.969 and an RMSE of 0.036. While these models yield excellent predictive accuracy, computational constraints often hinder their practical implementation. GPR, for instance, requires significant computational power and does not scale well with large datasets, making it less feasible for real-world applications. MARS-L's accuracy depends on proper feature selection, which adds complexity to model deployment. In contrast, LSIA balances high accuracy with computational efficiency, making it a more viable choice for large-scale geotechnical applications.

LSIA's superior performance is primarily due to its enhanced parameter optimization. Unlike traditional models that rely on manual tuning or grid search, LSIA fine-tuned the C and Gamma of LSSVR. This results in better convergence, improved generalization, and reduced overfitting. Using the RBF kernel further enhances LSIA's predictive capabilities by effectively capturing non-linear relationships in CBR prediction. In contrast, tree-based models like RF and LGBM may struggle with overfitting or underfitting when applied to complex datasets, leading to suboptimal predictions.

A key factor differentiating LSIA from its counterparts is its ability to balance accuracy and computational efficiency. While GPR achieves marginally better accuracy, its resource-intensive nature limits its scalability. LSIA, on the other hand, delivers high accuracy with lower computational demands, making it more practical for large datasets and real-world geotechnical applications. The model's robust generalization ability ensures that it remains reliable across diverse datasets, reducing the risk of overfitting and improving predictive stability.

Comparing LSIA with LSEM and LSRK, it is evident that LSIA consistently outperforms the other two hybrid models. While all three approaches benefit from hybrid optimization, LSIA's use of IAOA proves more effective than ESMA in LSEM and RKO in LSRK. This is reflected in LSIA achieving the highest R^2 and the lowest RMSE among the three, indicating that IAOA is better suited for optimizing LSSVR parameters. While LSEM and LSRK still show significant improvements over traditional models, their optimization strategies do not reach the same level of refinement as LSIA, explaining the slight performance gap.

In conclusion, LSIA stands out as a robust and efficient alternative for CBR prediction, surpassing most existing SOTA models. While GPR and MARS-L achieve high accuracy, their computational demands and feature selection dependencies limit their practicality. LSIA's hybrid optimization approach, leveraging IAOA, enhances both predictive accuracy and efficiency, making it a superior choice for geotechnical applications. The results validate that LSIA is a reliable and scalable solution capable of providing accurate CBR predictions while addressing the limitations observed in previous studies.

Table 5: Summary of previous studies related to CBR prediction.

Article	Model	Evaluator	
		R^2	RMSE
[18]	MLR	0.841	-
[19]	ANN	0.981	1.187
[20]	ANN	0.945	2.81
[21]	GPR	0.999	0.139
[22]	ANN	0.970	1.691
[23]	MARS-L	0.969	0.036
[24]	RF	0.98	1.43
[25]	LGBM	0.947	0.33
Present Study	LSIA	0.9932	1.1270

5 Conclusion

To ensure durable and flexible pavements, it is often necessary to use reliable techniques to assess or validate the California Bearing Ratio (CBR). However, the traditional method of determining the CBR of the subgrade can be challenging due to the significant time required for testing. As a result, there is a need to investigate other approaches, such as creating predictive models, to estimate the CBR of expansive soil subgrades. This justification has led to a greater usage of machine learning than human experimentation. This paper aims to provide an overview of LSSVR as a prevalent machine-learning technique for predicting CBR. Moreover, 3 meta-heuristic algorithms—IAOA, RKO, and ESMA—were combined with the proper model to create a hybrid model that would increase accuracy and reduce possible mistakes. In this study, several performance metrics containing R^2, $RMSE, MAE, SMAPE$, and SI, were applied to evaluate the effectiveness of the models in the train and test phases, in which 70% of samples belonged to training and 30% to testing phases. The evaluation of the achievements of the blended models was conducted using distinct criteria that were applied in the model selection process. As a result, the hybrid LSIA can obtain the highest R^2 with slight differences compared to the other two models. In addition, in RMSE, the LSIA achieved a 45% and 67% difference from LSEM and LSRK. Generally, it can be inferred that the IAOA model, when used with LSSVR, demonstrated superior performance than the other two models in both the training and testing phases.

The study demonstrated that the LSIA model outperforms the LSEM and LSRK models in predicting the CBR, achieving superior performance metrics such as high R^2 and low RMSE. While these results highlight LSIA's predictive accuracy, a more critical evaluation of its computational costs and practical applications within geotechnical engineering is necessary. Although LSIA offers improved accuracy, it may incur higher computational demands, which need to be weighed against its performance, especially in real-world scenarios where resources and time are limited. The manuscript should discuss the computational efficiency of LSIA compared to other methods, particularly regarding training time and resource usage, to help determine if the accuracy improvements justify these costs. In geotechnical contexts, LSIA could be particularly beneficial in projects with heterogeneous soil conditions, where traditional methods might not perform well. However, the paper should explore specific situations where LSIA could provide the greatest value, such as in projects requiring high accuracy and model robustness. Additionally, real-world case studies or field tests would further solidify the practical relevance of LSIA, demonstrating its utility across various soil types and conditions. Future work should include a detailed computational efficiency analysis of LSIA, particularly in comparison with other models, to determine its scalability for large-scale projects. Real-world applications and sensitivity analysis would help refine the model and make it more adaptable to diverse geotechnical datasets. Furthermore, exploring hybrid models that combine LSIA with other algorithms could offer a balance between accuracy and computational efficiency, making it more suitable for practical implementation. In conclusion, while LSIA shows promising potential in CBR prediction, a deeper exploration of its computational feasibility and real-world applicability will enhance its value for geotechnical engineering applications.

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Hybrid K-Nearest Neighbors Models with Metaheuristic Optimization for Predicting Undrained Shear Strength

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Around the world, soft soils can be found in many areas close to seas and rivers. These areas play an indispensable and crucial role in the development of government plans, especially in the population growth sector. Due to maintaining a weak shear power and vast settlement under the buildings, soft soils are considered problematic soil. The significant risks associated with building structures and infrastructures in soft soil are high, requiring engineers' extreme attention. It depends on undrained shear strength (USS) that the foundation of structures can bear in soft soil, and this factor vigorously controls the selection of soil improvement techniques. In recent years, there have been enhancements and extensions in the methodologies employed for estimating soil characteristics, including USS. These methods are divided into three main sections: Laboratory Testing, Field Testing, and Correlation with Other Soil Parameters. In recent research, data science techniques have created more reliable and accurate models for predicting USS. This study aims to apply the K-Nearest Neighbors (KNN) classifying method for predicting USS. Mountain Gazelle Optimizer (MGO) and Coronavirus Herd Immunity Optimizer (CHIO) appeal for developing hybrid models with KNN and facilitating accuracy enhancement. The dataset which utilized in this study contains four input variables including liquid limit (LL), plastic limit (PL), and sleeve friction (SF), overburden weight (OBW). Comparative analysis across all data phases reveals that the KNCH model, optimized using the CHIO, achieved superior predictive performance with the highest coefficient of determination (R^2 = 0.993), and the lowest values in root mean square error (RMSE = 85.19), mean squared error (MSE = 7256.15), normalized RMSE (NRMSE = 0.470), and scatter index (SI = 0.065). In contrast, the KNN model without optimization reported R^2 = 0.971, RMSE = 168.17, and SI = 0.132, while the KNMG model—optimized using the MGO—resulted in R^2 = 0.983, RMSE = 128.15, and SI = 0.101.

Povzetek: Raziskava uvaja hibridne modele KNN, optimizirane z metahevristikama CHIO in MGO, za napredno napovedovanje nedrenirane strižne trdnosti tal v geotehničnem inženirstvu.

1 Introduction

Construction of geotechnical structures like dam embankments, dikes, levees, as well as road embankments is a common challenge in most countries worldwide, particularly when such structures are situated on organic subsoils [1]. Due to the significant compressibility and low initial Undrained Shear Strength (USS) of organic soils, constructing even moderately-sized embankments become problematic in engineering practice. When designing embankments on such subsoils, determining the stability of the embankment and anticipating subsurface deformations are the main challenges. The embankment stability analysis during construction predominantly relies on the USS of organic soils [2,3].

Common field investigations include the Cone Penetration Test with Pore Pressure Measurement (CPTu) and the Vane Shear Test (VST) to assess the USS of soils. The VST utilizes cruciform blades rotated at a defined speed as per ASTM D2573-08 standards to determine USS values in saturated clay deposits, while the CPTu involves a 60° cone penetrometer with a friction sleeve, adhering to ASTM D-5778 standards, providing measurements of cone tip resistance (CR), sleeve friction (SF), and porewater pressure (PP). Dissipation tests are often conducted to evaluate equilibrium porewater pressure (pp_0) by halting cone penetration and measuring porewater pressure dissipation. Even if human errors are assumed to be reduced to zero in these experiments, they are time- and cost-consuming [4].

To overcome all issues, utilizing novel machine learning (ML) algorithms in various aspects of engineering geotechnical studies has experienced remarkable growth lately [5–8] . Among the vast number of research articles on applying machine learning models in geotechnical engineering published over the past years, approximately 70% have emerged within the last decade (data spanning from 1984 to 2019 [9]). A recent

comprehensive review article [10] provides an overview of the use of artificial neural networks (ANN) for estimating soil mechanical substances, particularly in terms of compressive and shear strength. [11–16]. support vector machines (SVM) and ANN have found application in forecasting bearing capacity for driven piles and settlement of shallow foundations [17,18]. These techniques have also been widely adopted for soil slope steadiness evaluation and estimation, including decision trees and logistic regression [19–22]. In geotechnical earthquake engineering, ANN and other deep learning frameworks were effectively employed to evaluate soil liquefaction potential [23–25]. Additionally, within the field of dynamic soil-foundation-structure interaction investigations, researchers have utilized multivariate linear regression and distance-weighted K-Nearest Neighbors (KNN) regression techniques to construct preliminary predictive models. These models aim to estimate seismic energy dissipation, permanent settlement, and the acceleration amplification ratio (which signifies the reduction in maximum acceleration transferred to the structure) for shallow foundations exhibiting rocking behaviour [26–28].

In geotechnical engineering, designers rely on crucial soil properties to accurately determine USS. These fundamental properties are also integral in developing predictive models through ML techniques. For example, the concept of soil plasticity, initially proposed by Atterberg in 1911, was introduced into soil mechanics by Casagrande in 1932 and further elaborated by Terzaghi and Peck in 1948. Soil behaviour is categorized based on water content (w), defined as the ratio of moisture mass to the mass of dry soil particles, resulting in four states: solid, semi-solid, plastic, and liquid. Two primary consistency limits are employed to characterize soil behaviour. The plastic limit (PL) is the minimum water content at which soil exhibits plastic deformation, which is irrecoverable deformation without failure. The liquid limit (LL) is defined as the minimum water content at which soil behaves as a viscous fluid, essentially marking the boundary where the shear strength of the soil is nearly zero [29]. The liquidity index (LI) normalizes soil's water content concerning its plastic and liquid limits. When the LI is less than zero, the soil exhibits brittle behaviour, falling into the categories of solid or semi-solid. Conversely, when the LI exceeds 1, the soil behaves like a liquid. In the literature, it has been documented that the USS of remoulded soil at the liquid limit can range from 0.5 to 1.7 kPa, with variations depending on soil types and testing apparatus or measurement methods [30].

This investigation's goal is to develop data-driven predictive models for soil USS utilizing supervised learning and non-linear ML techniques. Data from a 200 rock samples database consisting of sleeve friction (SF), LL, PL, and overburden weight (OBW) have been used to train, validate, and test machine learning models developed in this investigation. The non-linear, nonparametric ML algorithm considered is KNN. The performances of this single model are compared with the performance of optimized versions, which were developed using CHIO and MGO. The following sections explain the intake attributes and the theories of the ML methods in brief and their process of implementation in this research, provide performance evaluation parameters and present the major conclusions and outcomes of the research.

- **Justification for algorithms' selection**

In this study, the MGO and CHIO were selected to enhance the predictive performance of the KNN model due to their demonstrated efficiency in handling complex, nonlinear optimization problems. These recently developed metaheuristic algorithms offer strong exploration-exploitation balance, fast convergence, and robustness against local minima, making them suitable for hyperparameter tuning in machine learning models. Their unique mechanisms—MGO's predator-prey-inspired movement strategy and CHIO's immunity-based adaptation—provide diverse search capabilities and improved accuracy, which are critical in developing reliable predictive models for USS.

- **Novelties and Contributions**

The novelty and distinctiveness of this study, particularly in the context of USS prediction using ML, can be articulated through the following key contributions:

1. Pioneering Application of KNN-Based Models in USS Prediction: To the best of the author's knowledge, this study represents only the second documented academic attempt to employ KNN-based models for the prediction of USS of soils. This rare application underscores the innovative nature of the study, especially given the limited exploration of KNN in geotechnical engineering contexts, where more conventional regression-based or deep learning approaches are typically favored.
2. Development of Two Novel Hybrid Models with State-of-the-Art Optimization Algorithms: This research introduces two cutting-edge hybrid models—KNCH and KNMG—by integrating the KNN algorithm with two recently developed metaheuristic optimization techniques: the CHIO and the MGO, respectively. These algorithms have shown substantial promise in diverse domains for hyperparameter tuning and global search efficiency, and their application here represents a significant methodological
3. advancement for enhancing the predictive capability and convergence behavior of KNN models in civil engineering problems [31–33].
4. Robust Performance Evaluation Using Multiple Statistical Metrics: A comprehensive model evaluation framework is established through the implementation of five widely recognized statistical performance indicators: R^2, RMSE, MSE, NRMSE, and the SI. This multi-metric approach facilitates an in-depth and multi-dimensional performance assessment of the models, enabling rigorous benchmarking of their prediction quality, generalization capacity, and error distribution.

Table 1 reports the summary of comparing between previous publications.

Table 1: The summary of the literature review

Study	Dataset Size	Methodologies	Key Results	Limitations
[30]	~100+ laboratory-tested remoulded clay soil samples	Experimental investigation and empirical modeling based on Atterberg limits	- Reported that USS at liquid limit (LL) ranges between 0.5–1.7 kPa depending on soil type - Strong empirical correlation observed between USS and the Liquidity Index (LI)	- Not ML-based - Focused only on remoulded soils in specific consistency states - Limited generalizability across soil types
[12]	~150 samples	Multilayer ANN	- Showed ANN could outperform conventional empirical equations - Strong correlation between input features (e.g., PL, LL) and USS	- Overfitting risk due to small dataset - No feature importance analysis
[13]	~200 samples	Support Vector Machines (SVM)	- SVM accurately predicted soil cohesion - $R^2 \approx 0.9$ with optimized kernel parameters	- Highly sensitive to kernel selection - Requires tuning for different soil types
[14]	~180–220 data points	ANN (Feedforward)	- Developed regression-based ANN models - Achieved better accuracy than linear models	- Lacked uncertainty quantification - No real-time or field validation
[34]	300+ samples	ANN with cross-validation	- ANN demonstrated good generalization after k-fold validation - Applied in pile foundation design	- Focused on bearing capacity - Input features not aligned with USS prediction
[15]	~200 soil specimens	Hybrid SVM-GA (Genetic Algorithm)	- Combined SVM with GA for parameter tuning - RMSE reduced by ~15% compared to standalone SVM	- Computationally intensive - No interpretability analysis (e.g., SHAP or PCC)
[19]	~300 slope case studies	Decision Tree (DT), Random Forest (RF)	- Achieved classification accuracy > 90% - Identified top influencing features (e.g., angle, cohesion)	- Binary classification (stable/unstable) - Not suitable for continuous USS regression
[20]	GIS-based dataset (~500+ sites)	Logistic Regression (LR)	- Used for landslide hazard zonation - Provided probabilistic maps for decision-making	- Not designed for strength prediction - Model outputs are probabilities, not magnitudes
[21]	~400 data points	Decision Tree	- High interpretability - Good for categorizing soils by failure type	- Not regression-capable - May oversimplify nonlinear soil behavior
[22]	150–250 slope instances	SVM, DT, ANN	- Compared multiple ML algorithms - SVM performed best (AUC > 0.93)	- Application limited to classification - Soil shear strength not directly modeled

2 Materials and methodology

This section provides a comprehensive overview of the data preparation process, a detailed description of the K-Nearest Neighbors (KNN) model used as the baseline, and the implementation of the MGO and CHIO algorithms for optimization. Additionally, it outlines the evaluation metrics employed for performance assessment and presents the cross-validation results. These components are organized and discussed in detail across subsections 2.1 to 2.6.

2.1 Dataset description

To predict the undrained shear strength of soil, outstanding 200 sample records from publication [35] were categorized randomly into validation (15%), testing (15%), and training (70%) phases. Here, SF, LL, PL, and

OBW—five variables that can impact the USS's value—were taken into account as inputs. As the preprocessing tasks, the dataset is evaluated for miss values and no miss value is observed. In addition, the samples are randomized utilizing randperm method.

SF refers to the resistance a pile or shaft encounters as it is driven or inserted into the subsurface soil or rock. It arises due to the shear resistance between the surface of the pile or shaft and the surrounding soil or rock material. LL represents the moisture content at which soil shifts from a plastic to a semi-solid state, determined by the Casagrande cup test, while PL signifies the moisture content at which soil transitions from a plastic to a brittle state, determined through the plasticity index test. Finally, OBW is the total vertical load the soil or rock exerts above a specific point underground. Table 2 presents the statistical characteristics of the dependent input variables' maximum, minimum, average, and standard deviation values as well as USS's target variable.

The line-symbol plot in Figure 1 demonstrates the values of each input parameter and the output for 200 samples. As it is obvious, among input parameters, the broadest and narrowest range of values are related to the LL and SF, respectively. OBW illustrates more fluctuation, and USS as an output parameter fluctuates less with more values near 1000 (MPa). In addition, the correlation between input and output parameters is illustrated in Figure 2.

Table 2: The statistic properties of the input variable of USS.

Indicator	Variables				
	SF	LL	PL	OBW	USS
Max	1.400	133	50	3.640	5670
Min	0.020	24	12	0.030	100
Avg	0.425	63.49	27.48	1.569	1271.9
St. Dev.	0.289	19.886	6.940	0.824	968.61

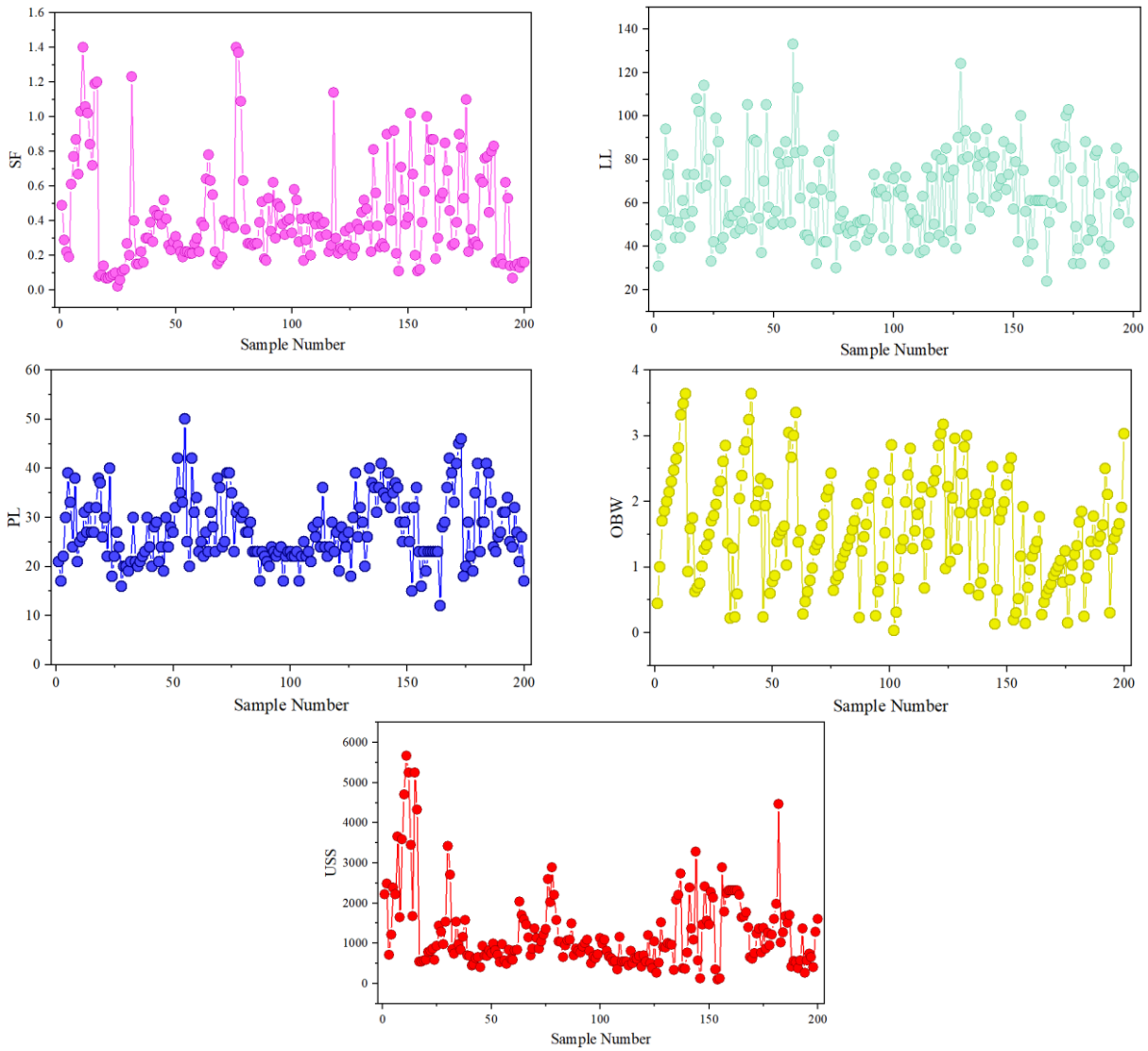


Figure 1: The Line-Symbol plot for input and output

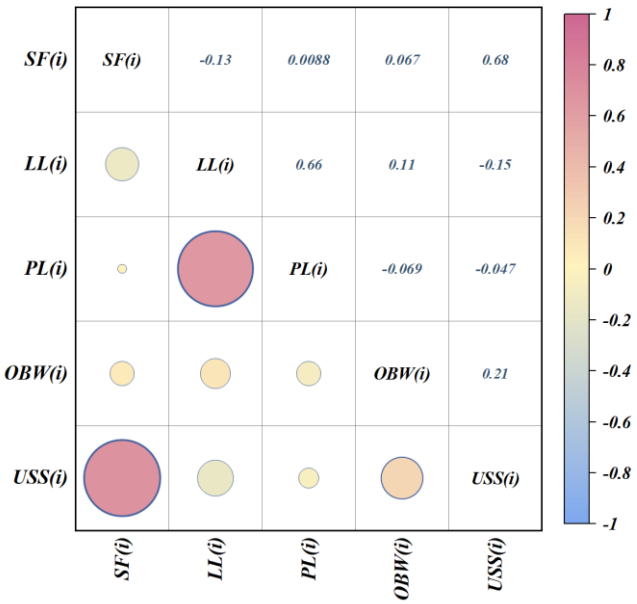


Figure 2: The Correlation plot for relationship between parameters.

The computational framework utilized in this study is optimized to meet both hardware and software requirements efficiently. At its core, the system operates on an Intel® Core™ i7-3770K CPU clocked at 3.50 GHz, paired with 16 GB of RAM to support seamless multitasking and high-performance operations. The system architecture is 64-bit, featuring an x64-based processor, and it runs on the Windows 11 Pro operating system, ensuring modern compatibility and robust functionality. Graphical processing is managed by an NVIDIA GeForce GT 640 GPU, which provides reliable support for rendering and visualization tasks. Storage needs are met with a 1-terabyte hard drive, offering ample capacity for large-scale data processing and storage. On the software front, Python serves as the primary programming environment. Machine learning implementations are facilitated through the scikit-learn library, while Pandas and NumPy are employed for data manipulation and analysis. For visualization purposes, Matplotlib is utilized to effectively present analytical results, forming a comprehensive and capable toolkit for data-driven applications.

2.2 Machine learning techniques

2.2.1 K-Nearest Neighbors (KNN)

The KNN algorithm is well known for its ease of use, simplicity, as well as effectiveness [36]. KNN is comparable to random forests (RF) and ANN in that it may be utilized in both regression and classification applications. The utilization of this technique offers several advantages:

1. It exhibits a clear and intelligible essence, which qualifies it for practical application.
2. When used for classification as well as regression, it can learn non-linear decision boundaries and becomes more versatile by allowing adjustment of the K value to define these boundaries.
3. In contrast to other algorithms, KNN doesn't require a specific training phase.
4. The technique utilizes a single hyperparameter, represented as K, simplifying the adjustment of other hyperparameters.

Finding a collection of K samples—often identified by a distance function—that show proximity to unknown samples within the calibration dataset is the basic idea behind KNN. Reaching this goal involves identifying groups of matching samples. To identify the classes of unidentified samples, KNN then computes the average of the response variables and compares the outcome to that of a set of K samples [37]. In this way, the KNN algorithm's selection of value for K is crucial to its effectiveness [38]. Equations (1) through (3) are the three distance functions that are used for this purpose in regression tasks to calculate the distances between neighboring data points:

$$F(e) = \sqrt{\sum_{i=0}^{f}(x_i - y_i)^2} \tag{1}$$

$$F(ma) = \sum_{i=0}^{f}|x_i - y_i| \tag{2}$$

$$F(mi) = \left(\sum_{i=0}^{f}(|x_i - y_i|)^q\right)^{\frac{1}{q}} \tag{3}$$

In this context, $F(e)$ denotes the Euclidean distance function, $F(ma)$ represents the Manhattan distance function, and $F(mi)$ stands for the Minkowski distance function. x_i and y_i That is, it concerns the ith dimension

of the data points x and y, where q is an order parameter utilized to calculate the distances between them.

2.2.2 Mountain gazelle optimizer (MGO)

In order to replicate the behavior of mountain gazelles, the MGO (Mountain Gazelle Optimization) algorithm divides them into three groups: territorial males, maternity herds, and bachelor males. It balances exploitation and exploration to approach optimal solutions, focusing on cost-effective individuals inspired by the least competitive gazelles among bachelor herds [39].

- **Territorial solitary males**

Upon maturing and gaining physical strength, male mountain gazelles establish solitary territories they vigorously defend. These territories are typically spaced apart, leading to confrontations and dominance battles over territory and access to females. Younger males seek to establish themselves and mate with females, while adult males staunchly protect their territories. Equation (4) serves as a model for these territories maintained by adult male gazelles.

$$TSM = male_{gzl} - \left|\left(ri_1 \times YH - ri_2 \times X(t)\right) \times F\right| \times Cof_r \tag{4}$$

Equation (4) describes $male_{gzl}$ as the situation vector shows the greatest universal resolution, which is the adult male. The variables ri_2 and ri_1 show arbitrary integers that can take on a value of either 1 or 2. YH denoted the coefficient vector of the young male herd and is obtained by Equation (5). Similarly, F is obtained by Equation (6). During every iteration, the randomly chosen coefficient vector Cof_r is updated and utilized to boost the search power. Equation (7) can be employed to define this coefficient vector.

$$YH = X_{ra} \times \lfloor r_1 \rfloor + M_{pr} \times \lceil r_2 \rceil, \quad ra = \left\{\left\lceil \frac{N}{3} \right\rceil \ldots N\right\} \tag{5}$$

Here, X_{ra} denotes an arbitrary resolution (young male) in ra's range. M_{pr} refers to the search experts' mean amount, which is equal to $\left\lceil \frac{N}{3} \right\rceil$ And N shows the whole gazelles' amount when r_1 and r_2 show arbitrary amounts in [0,1].

$$F = N_1(D) \times \exp\left(2 - Iter \times \left(\frac{2}{MaxIter}\right)\right) \tag{6}$$

Equation (6) incorporates various problem-specific variables, incorporating the use of the exponential function (exp) and N_1, a number chosen at random from a standard distribution. It also considers the current iteration ($Iter$) and the total number of iterations ($MaxIter$) in the process.

$$Cof_i = \begin{cases} (x+1) + r_3, \\ x \times N_2(D), \\ r_4(D), \\ N_3(D) \times N_4(D)^2 \times \cos\left((r_4 \times 2) \times N_3(D)\right), \end{cases} \tag{7}$$

$$x = -1 + Iter \times \left(\frac{-1}{MaxIter}\right) \tag{8}$$

Additionally, r_3, r_4, and $rand$ are random numbers from 0 to 1. The random numbersN_2, N_3, and N_4 are related to the dimensions of the problem and are drawn from a standard distribution. $Iter$ represents the number of iterations that are being performed, and $MaxIter$ is the number of iterations that are to be executed.

- **Maternity herds**

Maternity herds are crucial for producing robust male gazelles. Equation (9) mathematically describes the interaction between male gazelles assisting in childbirth and juvenile guys trying to mate with females.

$$MH = \left(YH + Cof_{1,r}\right) + (ri_3 \times male_{gzl} - ri_4 \times X_{rand}) \times Cof_{1,r} \tag{9}$$

Here, YH signifies the influence factor vector of adolescent males. Coefficient vectors $Cof_{2,r}$ and $Cof_{3,r}$ are independently established through random selection. Two random integers, ri_3 and ri_4, can have values of 1 or 2. The maximum universal resolution (adult male) in the current iteration was indicated by the symbol $male_{gzl}$. In the end, the position vector of a gazelle selected at random from the entire population is represented by X_{rand}.

- **Bachelor male herds**

As male gazelles mature, they establish territories and compete intensely with younger and with adult males in the mating chase for access to females and territory dominance, as mathematically depicted in Equation (10).

$$YMH = (X(t) - D) + (ri_5 \times male_{gazelle} - ri_6 \times YH) \times Cof_r \tag{10}$$

$$D = (|X(t)| + |male_{gzl}|) \times (2 \times r_6 - 1) \tag{11}$$

Where, $X(t)$ indicates the position vector of the Gazelle in the current iteration. The variables ri_5 and ri_6 are random integers that can take a value of either 1 or 2. The position vector of the male Gazelle (the best solution) is denoted by $male_{gzl}$. Another random number between 0 and 1 is r_6.

- **Migration to search for food**

Mountain gazelles have a strong tendency for food foraging, which sometimes involves extensive journeys to locate suitable food sources or engage in migration. Their exceptional running speed and jumping abilities are

crucial in this behaviour, as mathematically represented in Equation (12).

$$MSF = (ul - ll) \times r_7 + ll \quad (12)$$

Where ul and ll define the upper and lower problem limits in order. Moreover, r_7 is a randomly selected integer within the range [0,1]. The Algorithm 1 is the pseudocode for the MGO. In addition, the flowchart of MGO illustrated in Figure 3.

Algorithm 1. Pseudocode of MGO.

```
MGO setting
Inputs: The population size N and maximum number of iterations I
Outputs: Gazelle's location and fitness potential

Initialization
Create a random population using Xi (i = 1, 2, ..., N)
Calculate Gazelle's fitness level.

While (stopping condition is not met) do
    for (each Gazelle Xi) do
        % Single male
        Calculate TSM
        Mother and child herd
        Calculate MH
        Young male herd
        Calculate YMH
        Migration to search for food
        Calculate MSF
        Calculate the fitness values of TSM, MH, YMH, and MSF, then add them to the habitat
    end for
    Sort the entire population in ascending order
    Update bestGazelle
    Save the N Best Gazelles in the Max number of population
end while

Return XBestGazelle, best Fitness
```

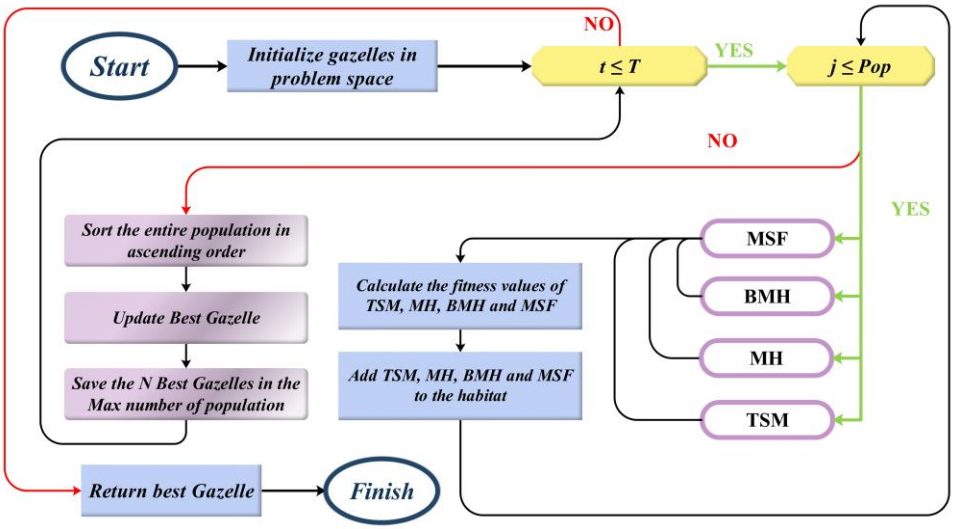


Figure 3: The flowchart of the MGO algorithm.

2.2.3 Coronavirus herd immunity optimizer (CHIO)

Six main stages of the CHIO algorithm are described below [40]:

Step (1): At the start, the CHIO parameters are configured along with the initiation of the optimization issue. This includes constructing the optimization issue with the utilization of an objective function, which will be further detailed below.

$$Min\ f(x)\ \ x \in [LB, UB] \tag{13}$$

Here, the immunity rate, represented by the objective function $f(x)$, is evaluated for a particular instance (or person) represented by $x = (x_1, x_2, \dots, x_n)$, where each x_i relates to the gene (or decision variable) linked to the index i. Each individual contains a total of n genes and the values for each gene, x_i, are confined within the range [LB, UB], determined by their respective lower (LB) and upper bounds (UB).

The CHIO system consists of two control parameters and four algorithmic parameters.

The algorithm parameters are as follows:

- I_0: Stands for the initial count of infection cases, initially set to one.
- $Max - Itr$: Specifies the maximum number of iterations.
- Ps: Governs the population size.
- n: Represents the dimensionality of the problem.

At this stage, two crucial control parameters for CHIO are set to their initial values:

- The Basic Reproduction Rate BR_r, which quantifies viral pandemic transmission and significantly influences the decisions made by CHIO operators.
- The outcome of infected individuals is significantly influenced by the maximum age for infection (Max_{Age}). Individuals who reach this age are documented as having recovered or having passed away due to the illness.

Step (2): This stage aims to establish a population possessing herd immunity. It commences by generating a set of cases equivalent to the capacity of the host immune system (Ps). These instances are subsequently kept in the population classified as persons with herd immunity (P_{HI}) in a matrix-sized $n \times Ps$, as elaborated below:

$$P_{HI} = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_n^1 \\ x_1^2 & x_2^2 & \cdots & x_n^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^{Ps} & x_2^{Ps} & \cdots & x_n^{Ps} \end{bmatrix} \tag{14}$$

In this step, each casex_j is generated using the formula $x_i^j = LB_i + (UB_i - LB_i) \times U(0,1)$, for all $i = 1,2, \dots, n$. Additionally, a status vector (S) of length Ps is initialized for all cases in P_{HI}, with values of 0 indicating susceptibility and 1 indicating infection. With a count equal to I_0, the initial number of units in set S with a value of 1 is created at random.

Step (3): The genes (x_i^j) in each case x_j can experience stability or be influenced by social distancing measures, depending on three rules defined by the percentage of the Basic Reproduction Rate (BR_r).

$$x_i^j(t+1) \leftarrow \begin{cases} x_i^j(t) & r \geq B \\ C\left(x_i^j(t)\right) & r < \frac{1}{3} \times B.\ //infected\ case \\ N\left(x_i^j(t)\right) & r < \frac{2}{3} \times B.\ //susceptible\ case \\ R\left(x_i^j(t)\right) & r < B.\ //immuned\ case \end{cases} \tag{15}$$

A variable "r" generates a random number from zero to one, and B stands for BR_r. The three regulations set out the following terms and conditions.

$infected\ case$: When $r \in [0, \frac{1}{3}B)$, the impact of social distance on the gene expression $x_i^j(t+1)$ relies on the difference between the gene expression of an infected case x^m and the present gene expression, which is defined as follows:

$$x_i^j(t+1) = C\left(x_i^j(t)\right) \tag{16}$$

Where:

$$C\left(x_i^j(t)\right) = x_i^j(t) + r \times (x_i^j(t) - x_i^c(t)) \tag{17}$$

The status vector (S), where c denotes the set of i values for which S_i equals 1, determines the value of $x_i^c(t)$, which is selected at random from an infected case x^c.

$susceptible\ case$: The gene value $x_i^j(t+1)$ falls within the range of $r \in [\frac{1}{3}B, \frac{2}{3}B)$, and it is influenced by social distancing measures. These measures are determined by the difference between the current gene and a gene selected from a susceptible case x^m, as elaborated below:

$$x_i^j(t+1) = N\left(x_i^j(t)\right) \tag{18}$$

Where:

$$N\left(x_i^j(t)\right) = x_i^j(t) + r \times (x_i^j(t) - x_i^m(t)) \tag{19}$$

From a vulnerable situation x^m specified by the status vector (S), where m is the set of i values where S_i equals 0, $x_i^m(t)$is a randomly selected value.

$Immuned\ case$: The gene value $x_i^j(t+1)$ within the range of $r \in [\frac{2}{3}B, B)$, is modified to social distancing measures, which are influenced by the disparity between the current gene and a gene selected from a susceptible case x^ω as described:

$$x_i^j(t+1) = R\left(x_i^j(t)\right) \tag{20}$$

Where:

$$R\left(x_i^j(t)\right) = x_i^j(t) + r \times (x_i^j(t) - x_i^\omega(t)) \tag{21}$$

In a susceptible situation x^ω, which is defined by the status vector (S), $x_i^\omega(t)$ is a randomly selected value such that $f(x^\omega) = \min_{j \sim \{k | S_k = 2\}} f(x^j)$.

Step (4): The immunity rate, denoted as $f(x^j(t+1))$, is computed for each new case, $x^j(t+1)$. If the new rate is superior, meaning when $f(x^j(t+1)) < f(x^j(t))$, the current case $x^j(t)$ is replaced with a new one. In cases where S_j equals 1, the age vector A_j increases by one. The status vector (S_j) is updated for each individual (x^j) based

on the herd immunity threshold, as determined by the subsequent equation:

$$S_j \leftarrow \begin{cases} 1\ f\left(x^j(t+1)\right) < \dfrac{f(x)^j(t+1)}{\Delta f(x)} \wedge S_j = 0 \wedge is_corona(x^j(t+1)) \\ 2\ f\left(x^j(t+1)\right) > \dfrac{f(x)^j(t+1)}{\Delta f(x)} \wedge S_j = 1 \end{cases} \quad (22)$$

Here's the term: $is_corona(x^j(t+1))$ is given a value of 1 if the condition is inherited by the newly diagnosed case $x^j(t+1)$ from any previously infected case. The population's mean immunity rates are represented by the symbol$\Delta f(x)$, which is defined as$\frac{\sum_{i=1}^{Ps} f(x_i)}{Ps}$.

Step (5): When a person who has developed a certain illness and is classified as a case (with $S_j = 1$), and their immunity rate $f\left(x^j(t+1)\right)$ stays constant for a predetermined number of iterations as given by the parameter Max_Age $(i.e., A_j \geq Max_{Age})$, then the case is classed as a fatality.

Then, it is entirely recreated with $x^j(t+1) = LB_i + (UB_i - LB_i) \times U(0,1)$ for all $i = 1,2,\ldots,n$. Additionally, both A_j and S_j values are set to zero.

Step (6): The CHIO framework advances from $Step$ 3 to $Step$ 6 until it fulfils a pre-established termination condition, often set by a maximum iteration threshold. The population comprises a considerably larger number of susceptible and immune individuals than the population itself, and no further infections are occurring. Figure 4 displays the flowchart of the CHIO.

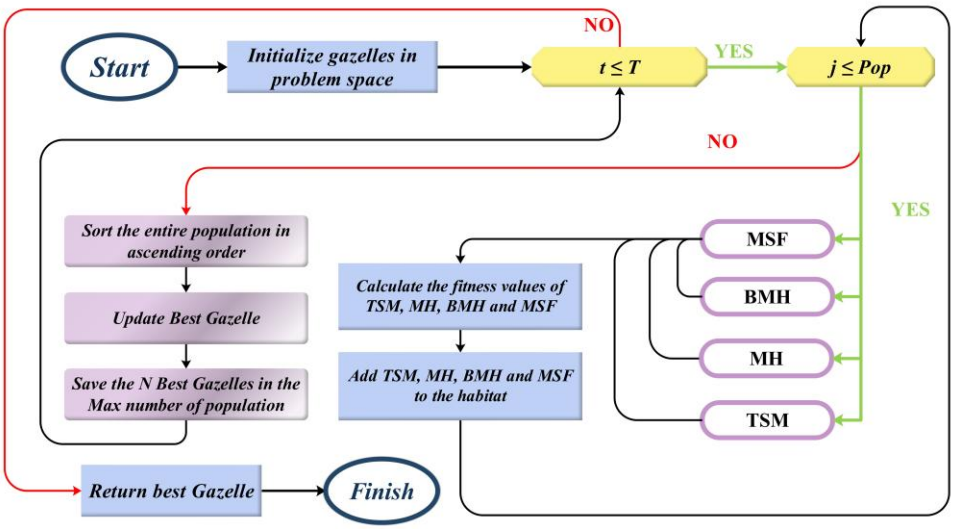


Figure 4: The flowchart of the CHIO algorithm.

2.3 K-Fold cross validation

To ensure robust evaluation of the prediction model, this study adopts the k-fold cross-validation (KCV) technique—a widely accepted and systematic approach to model validation. In k-fold cross-validation, the dataset is divided into *k* equally sized folds, where each subset is used once as the testing set while the remaining *k-1* subsets serve as the training set. This cycle is repeated *k* times, ensuring that every data point is used for both training and testing exactly once.

In this work, 5-fold cross-validation (k = *5*) is employed. The dataset is partitioned into five equal parts, and the algorithm is executed over five iterations. In each iteration, one-fold is designated for testing and the remaining four for training. The performance metrics across all five iterations are then averaged to provide a comprehensive assessment of the model's predictive capabilities.

As illustrated in Figure 5, the evaluation of the KNN model reveals that the fifth fold outperformed the others, achieving the highest coefficient of determination (R^2 = 0.971) and the lowest root mean squared error (RMSE = 168.23), marking it as the most optimal split.

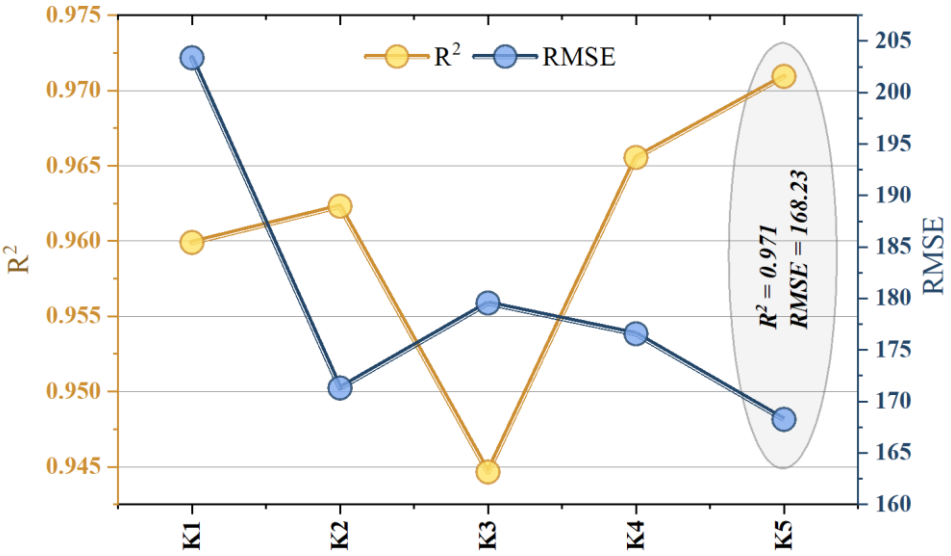


Figure 5: The results of 5-Fold Cross validation.

2.4 Metrics for performance assessment

To evaluate the performance and predictive accuracy of the developed models, a set of widely accepted statistical metrics are employed, each offering unique insight into different aspects of model behavior in regression tasks. The selection of these metrics—R², RMSE, NRMSE, MSE, and SI—is based on their proven effectiveness and interpretability in capturing model accuracy, error magnitude, relative performance, and data dispersion. These indicators are particularly suitable for this study, which involves continuous prediction of geotechnical properties, where both absolute and relative errors are of interest. While alternative metrics (e.g., MAE, MAPE) were considered, the chosen set offers a well-rounded, interpretable, and comprehensive assessment framework.

Coefficient of Determination (R²): This metric quantifies the proportion of variance in the observed data that is predictable from the model. It captures the strength and direction of the linear relationship between observed and predicted values. A higher R² indicates better model fit. It is defined as:

$$R^2 = \left(\frac{\sum_{i=1}^{n}(t_i - \bar{w})(v_i - \bar{v})}{\sqrt{[\sum_{i=1}^{n}(v_i - w)^2][\sum_{i=1}^{n}(v_i - \bar{v})^2]}} \right)^2 \quad (23)$$

Root Mean Square Error (RMSE): RMSE measures the average magnitude of prediction errors, offering an intuitive understanding of error in the same units as the target variable. It is particularly sensitive to large deviations, making it effective for detecting significant outliers:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(v_i - w_i)^2} \quad (24)$$

Normalized Root Mean Square Error (NRMSE): This is a scale-independent version of RMSE, enabling comparison across datasets or models with differing output ranges. It provides a normalized perspective on model performance:

$$\text{NRMSE} = \sqrt{\frac{\frac{1}{n}\sum_{i=1}^{n}(v_i - w_i)^2}{\sum_{i=1}^{n}(w_i)^2}} \quad (25)$$

Mean Squared Error (MSE): As the square of the standard deviation of prediction errors, MSE penalizes larger errors more severely, thus highlighting models that consistently produce significant deviations:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(v_i - w_i)^2 \quad (26)$$

Scatter Index (SI): SI measures the dispersion of the prediction errors relative to the mean observed value, providing a normalized indicator of how tightly predictions cluster around the true values. It is particularly useful for comparing performance across datasets with different scales:

$$SI = \frac{RMSE}{w_i} \quad (27)$$

Together, these metrics offer a comprehensive evaluation of both the absolute accuracy and relative performance of the predictive models, ensuring robust, multi-faceted performance validation.

In all the above equations:

n: number of samples,
v_i: predicted value,
$\bar{v}$: average predicted value,
w_i: experimentally measured value,
$\bar{w}$: average experimentally measured value.

3 Results

The primary objective of this study was to investigate the reliability of a single KNN model and optimized versions based on MGO and CHIO in predicting the Undrained Shear strength (USS) of soils. To achieve this goal, the models were divided into three categories: a training set, a

validation set, and a testing set, with 70%, 15%, and 15% of the models, respectively. Subsequently, the precision of each model in forecasting the USS was evaluated based on five evaluation metrics, and the results were presented through comparative charts and graphs, as presented in the following sections.

3.1 Results of hyperparameters and convergence curves

Effective hyperparameter tuning plays a critical role in enhancing the performance and generalization capability of machine learning models. While several strategies exist—including manual tuning, grid search, random search, and Bayesian optimization—the choice of method often depends on model complexity, the number of tunable parameters, computational resources, and time constraints.

In this study, a random search strategy was adopted for hyperparameter optimization due to its efficiency in exploring high-dimensional spaces without exhaustive computation. This method randomly samples combinations from predefined hyperparameter ranges, increasing the likelihood of identifying optimal configurations with reduced evaluation overhead.

As summarized in Table 3, the hyperparameter search focused on tuning three key parameters for the KNN-based hybrid models (KNCH and KNMG): n_neighbors, leaf_size, and P. These settings were varied systematically to maximize model performance while maintaining computational efficiency.

Table 3: The result of developed models for KNN

Hyperparameters	Hybrid Models	
	KNCH	KNMG
n_neighbors	14	20
leaf_size	958	736
p	813	905

Tracking RMSE over iterations is a common strategy to monitor how well a machine learning model is learning. Convergence plots help visualize this process by revealing trends in error reduction and indicating the model's ability to reach an optimal state.

As shown in Figure 6, the convergence performance of two hybrid models—KNCH and KNMG—was analyzed across 200 iterations. The KNCH model displayed a consistent downward trajectory in RMSE, ultimately stabilizing around 60, which points to efficient learning and robust optimization. On the other hand, KNMG started with a higher RMSE and leveled off closer to 90, reflecting a comparatively slower convergence.

These findings clearly demonstrate the superior convergence efficiency of KNCH over KNMG, making it a more promising candidate for modeling under the given setup.

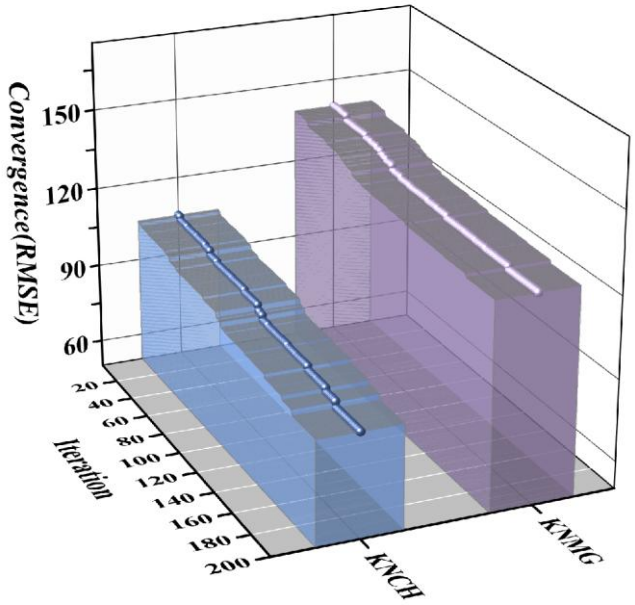


Figure 6: The Convergence curves for hybrid model

3.2 Results of evaluation metrics for models

This section compares the employed models' productivity by utilizing five statistical evaluators, R^2, RMSE, MSE, NRMSE, and SI, as depicted in Table 4. In terms of R^2, it is evident that the best result is for the KNCH in the training, validation, and testing parts, in which R^2 is 0.993, 0.987, and 0.977, respectively. Among the three models, KNCH consistently achieved the best results across the training, validation, and testing phases, with R^2 values of 0.993, 0.987, and 0.977, respectively. It is important to note that R^2 values in the testing phase are naturally lower than in the training phase, as the testing process is performed solely on unseen input data, without access to the corresponding output values. In contrast, during training, the model learns from both inputs and known outputs, allowing it to optimize its parameters. Therefore, this drop does not necessarily indicate improper training; rather, it reflects the realistic challenges of generalizing to new data. The relatively small decline in KNCH's R^2 values indicates strong generalization capability, especially when compared to KNMG (R^2: 0.985 → 0.976 → 0.967) and KNN (R^2: 0.975 → 0.958 → 0.950), where larger performance gaps are evident.

Comparing values of the SI in which lower values mean the highest model accuracy, it is evident that the optimal value of 0.065 was obtained in the validation phase of the KNCH, while this value for KNMG and KNN was approximately 50% and 30% higher. RMSE, NRMSE, and MSE outcomes demonstrate that the KNCH with the least error values ($RMSE = 85.192$, $NRMSE = 0.470$, and $MSE = 7259.15$) exhibited the highest level of performance, while KNMG and KNN placed second and third in rank, respectively.

Table 4: The result of developed models for KNN.

Phase	Model	Index values							
		RMSE	R^2	MSE	NRMSE	SI	Confidence Interval-lower	Confidence Interval-upper	St. dev of Errors
Train	KNN	163.81	0.975	26866	1.171	0.134	22163	34447	21.909
	KNCH	85.19	0.993	7259	0.609	0.070	6374	9907	10.991
	KNMG	123.05	0.985	15131	0.879	0.101	12756	19827	16.296
Validation	KNN	173.38	0.958	30061	5.779	0.106	20698	76344	19.327
	KNCH	106.90	0.987	11428	3.563	0.065	7028	25922	11.461
	KNMG	137.24	0.976	18835	4.575	0.084	9137	33701	14.011
Test	KNN	182.35	0.950	33252	6.078	0.159	19319	71260	26.407
	KNCH	116.62	0.977	13600	3.887	0.102	8554	31552	14.600
	KNMG	141.40	0.967	19994	4.713	0.123	12056	44469	19.458
All	KNN	168.17	0.971	28303	0.841	0.132	23571	34951	22.325
	KNCH	93.99	0.991	8836	0.470	0.074	7358	10911	11.701
	KNMG	128.15	0.983	16416	0.641	0.101	13623	20201	16.620

Figure 7 presents scatter plots that depict the relationship between the predicted USS values and their corresponding experimentally measured values for all three models across the training, validation, and testing phases. These plots serve as a visual diagnostic tool to evaluate both the accuracy and consistency of model predictions.

The x-axis represents the actual (measured) USS values, while the y-axis corresponds to the predicted values, adhering to standard regression visualization conventions. Each subplot also incorporates three key graphical elements:

1. A diagonal reference line (Y = X), representing perfect predictions where predicted values exactly match measured values.
2. A best-fit linear regression line, indicating the actual trend followed by the predictions.
3. Two boundary lines (Y = 0.9X and Y = 1.1X), denoting a ±10% margin of error—used to assess the practical range within which most predictions fall.

The inclusion of Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) values in each panel quantitatively supports the scatter distributions. RMSE measures the average magnitude of prediction errors, with lower values indicating less dispersion and higher data point density around the ideal fit. R^2 reflects the proportion of variance explained by the model; values closer to 1 imply a stronger correlation and tighter clustering of data along the ideal line.

Among the three models, KNCH demonstrates superior performance, with the highest R^2 values of 0.993 (training), 0.987 (validation), and 0.977 (testing). These results show a strong linear agreement between predicted and measured values. Concurrently, it exhibits the lowest RMSE values of 85.19, 106.90, and 116.62, respectively, indicating minimal prediction error and more compact clustering of data points.

While some overlap of data points is observed—due to the relatively narrow range of USS values in the dataset—this visualization remains valuable in confirming both the accuracy and consistency of the KNCH model across different data splits. Future work may incorporate density plots or zoomed views to improve interpretability when data point congestion is high.

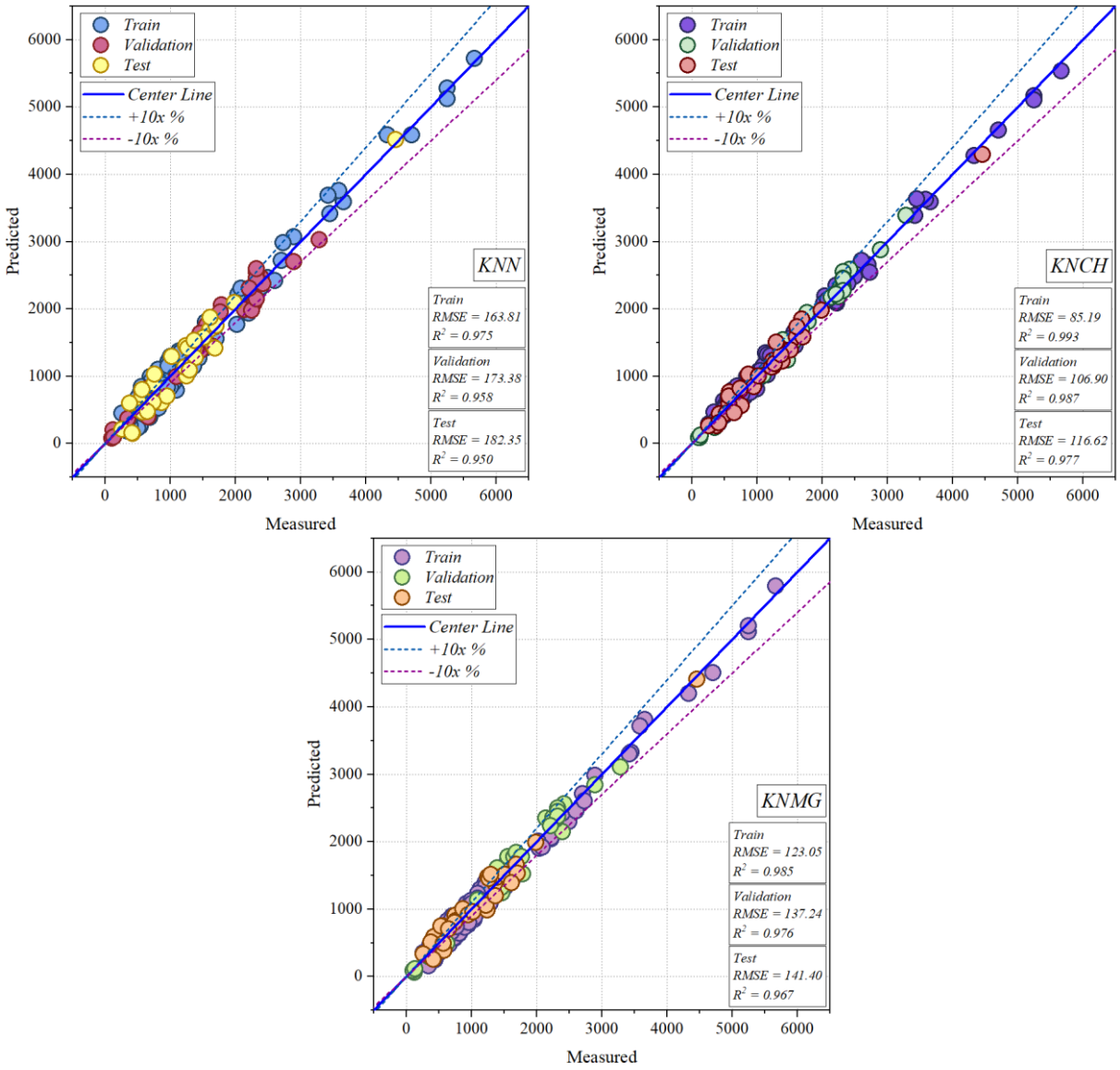


Figure 7: The scatter plot for developed hybrid models

The bar chart in Figure 8 presents a visual comparison of R^2, RMSE, and NRMSE (vertical axes) for three developed models in divided phases of training, validation, and testing (horizontal axes). Differences between R^2 values for the two hybrid models are marginal, with KNCH being better than KNMG, but KNN has a noticeable 3% difference with them. The discrepancy of models in the case of error values is more remarkable, especially in RMSE, in which the maximum value of 163.814 related to the KNN is almost twice the minimum value of 85.192 related to the KNCH model. Turning to the NRMSE charts, again, the same pattern as mentioned for RMSE is clear there. Also, corresponding values of NRMSE in validation and testing parts are 5 to 6-fold higher than that for the training part.

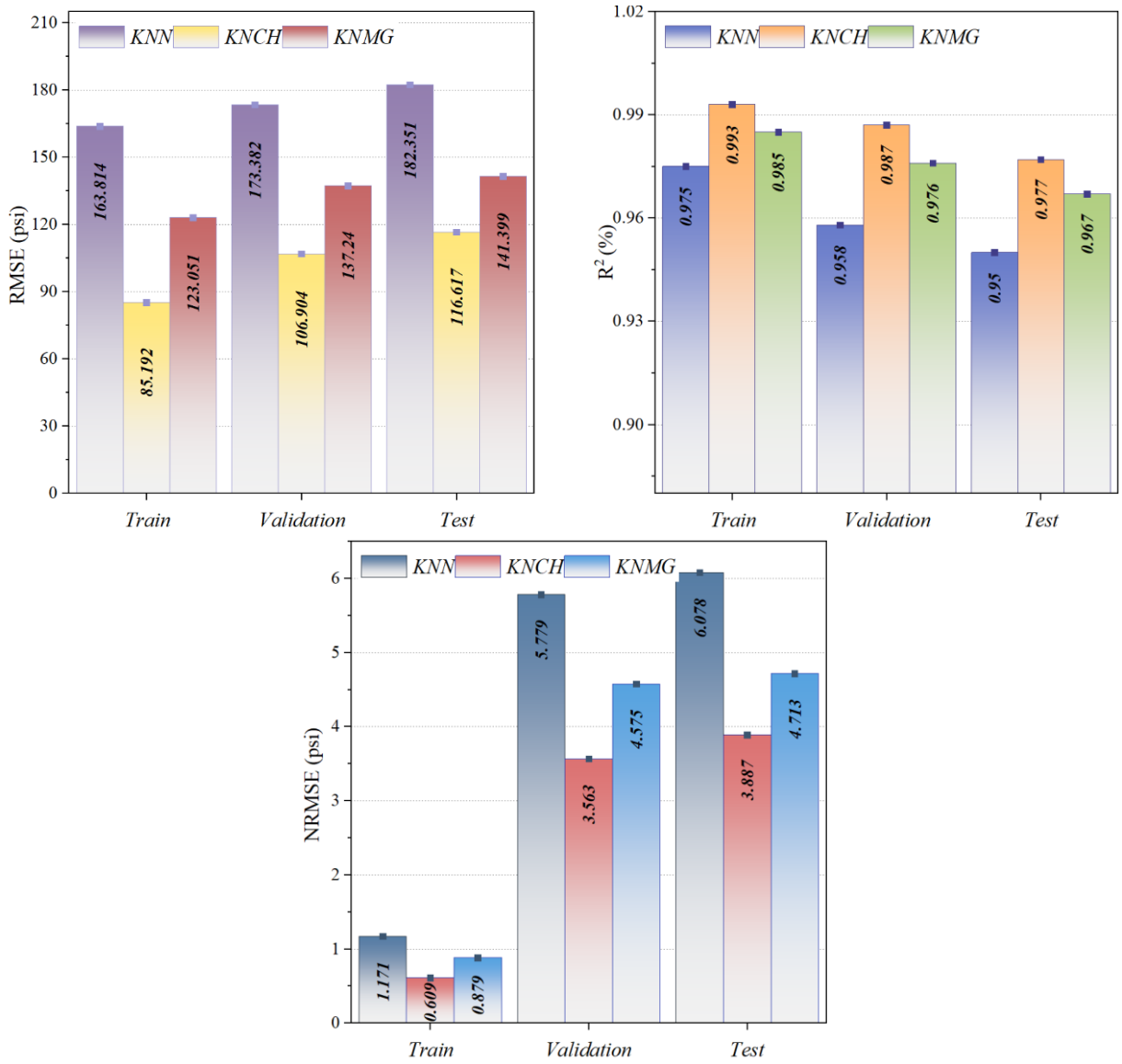
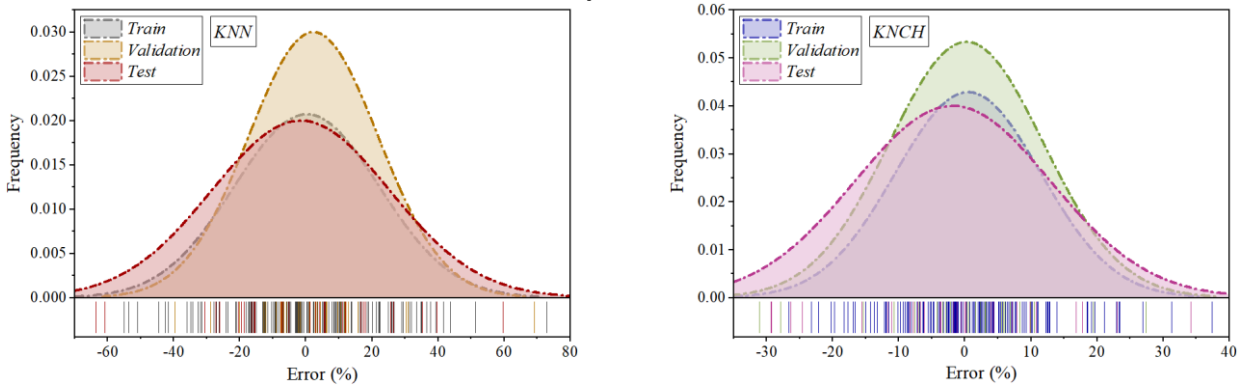


Figure 8: Comparison between models based on RMSE, R2, NRMSE

The normal distribution plot in Figure 9 exemplifies a graphical analysis of errors for the KNN, KNCH, and KNMG models. As the error range of KNN is more widely spread and diagrams related to the KNCH are more narrow bell-shaped ones, KNN and KNCH respective are less and more accurate models.



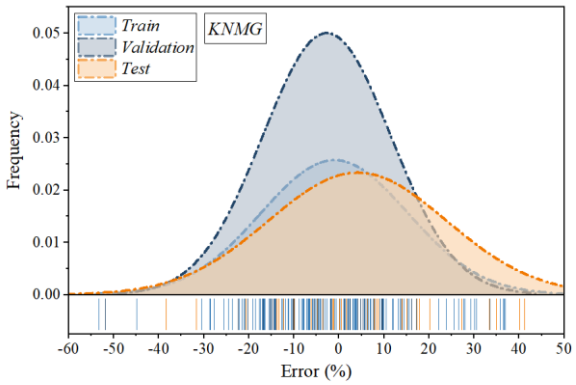


Figure 9: The error percentage for the models based on the normal distribution plot.

Figure 10 presents a comprehensive visualization of percentage prediction errors across all 200 data samples for the three evaluated models—KNN (baseline), KNCH (CHIO-optimized KNN), and KNMG (MGO-optimized KNN)—during the training, validation, and testing phases. This line plot was intentionally chosen for its ability to visually capture the behavior and variability of each model's prediction errors across individual samples, offering deeper insights beyond aggregate statistical metrics such as RMSE or R^2. The x-axis represents the sample number (1–200), while the y-axis indicates the prediction error (%). This enables a sequential view of how the models performed on each data point. The three vertical dashed lines divide the dataset into its respective training, validation, and testing partitions, which were used consistently across all models.

The baseline KNN model shows significant fluctuations and a tendency toward larger error spikes, especially in the training and validation phases. The maximum error value of 72.8%, highlighted in red, indicates susceptibility to outliers or poor generalization on certain samples. The KNCH model exhibits the most stable error profile, with error values closely clustered around zero and minimal large deviations, especially in the test phase. This suggests a higher predictive reliability and generalization capability. The KNMG model demonstrates performance improvements over the original KNN but displays slightly more variability than KNCH, indicating moderate robustness.

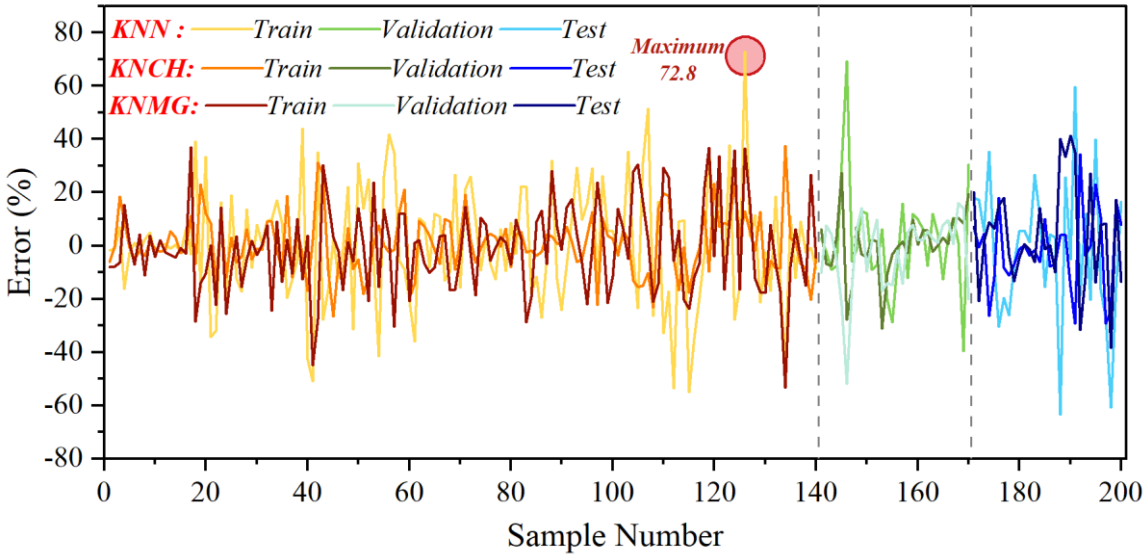


Figure 10: The Line plot for errors of the developed models.

- **Statistical significance test based on wilcoxon**

Table 5 summarizes the outcomes of the Wilcoxon signed-rank test, which was employed to statistically evaluate the performance differences among the developed models. The test was conducted to determine whether there were significant differences in the distributions of prediction errors.

According to the results, none of the models—KNN_MGO, KNN_CHIO, and KNN—show statistically significant differences, as all p-values are well above the 0.05 threshold. Specifically, the KNN_CHIO model yielded the highest p-value (0.882), followed by KNN (0.668) and KNN_MGO (0.347). The corresponding test statistics (9280, 9929, and 9699, respectively) further support the consistency in performance across these models.

These findings indicate that, under the given conditions, the predictive outputs of the three models are not significantly different from each other in a statistical sense.

Table 5: The result of Wilcoxon test.

Model	P-value	Statistics
KNN_MGO	0.347	9280
KNN_CHIO	0.882	9929
KNN	0.668	9699

- **Comparison with previous studies**

Table 6 presents a comparative analysis between the results of the present study and several recent state-of-the-art articles focused on predicting USS using machine learning techniques. The proposed KNN model in this study, trained on 200 samples using a limited yet effective set of inputs—LL, PL, SF, and OBW—achieved an excellent coefficient of determination ($R^2 = 0.993$). While the RMSE value (85.19) appears higher compared to other studies, it is important to consider that the scale and units of output values may differ, influencing RMSE interpretation.

In comparison, Zarei et al. [41] attained a slightly higher R^2 of 0.9975 using a deep neural network (DNN) with a more complex input set, albeit on a smaller dataset (72 samples). Zhang et al. [42] utilized the XGBoost model on a larger dataset (304 samples) and reported a lower R^2 (0.92), indicating that while their RMSE (2.38) was lower, the model's overall explanatory power was not as strong. Pham et al. [43] applied a hybrid RF-PSO model and obtained an R^2 of 0.89 with an impressively low RMSE (0.453), reflecting a trade-off between error minimization and data generalization. Elsawy et al. [44] implemented a Fine Gaussian Support Vector Regression (SVR), yielding strong performance ($R^2 = 0.96$; RMSE = 1.65) based on 111 data points.

Overall, the present study demonstrates competitive predictive accuracy using fewer input variables and a simpler model, underscoring its practicality and efficiency for real-world geotechnical applications. The high R^2 value confirms the model's robustness, despite RMSE differences which arising from dataset scaling or units of output.

Table 6: The Comparison between the results of present study and available articles.

Article	Dataset size	Inputs	Model	Metrics	
				R^2	RMSE
Zarei et al. [41]	72	vertical stress, percentage of the crushed tire, percentage of clay, size of clay, specific gravity of tires, Liquid limit, Plastic limit and Specific gravity of clay samples	DNN	0.9975	2.42
Zhang et al. [42]	304	vertical effective stress, pre-consolidation stress, liquid limit, plastic limit, and natural water content	XGBoost	0.92	2.38
Pham et al. [43]	127	Clay content, Water content, Specific gravity, Void ratio, Liquid limit, and Plastic limit	RF-PSO	0.89	0.453
Elsawy et al. [44]	111	natural water content, dry unit weight, liquid limit, plasticity index, consistency index, void ratio, specific gravity, and pocket penetration shear	Fine Gaussian SVR	0.96	1.65
Present study	**200**	**liquid limit (LL), plastic limit (PL), and sleeve friction (SF), overburden weight (OBW)**	**KNN**	**0.993**	**85.19**

4 Discussion

4.1 Practical implications

The findings of this study have direct relevance to geotechnical engineering, particularly in regions where soft soils are prevalent, such as coastal and riverine zones. By accurately predicting undrained shear strength (USS) using easily measurable soil parameters (LL, PL, SF, and OBW), engineers can make more informed decisions without relying solely on time-consuming and expensive laboratory or field tests. The hybrid models, especially KNCH, offer a computationally efficient alternative that retains high predictive accuracy, making them suitable for integration into early-stage geotechnical investigations, feasibility assessments, and large-scale infrastructure planning. Moreover, these models can be embedded into software tools or decision-support systems, enhancing design safety and reducing costs associated with soil characterization.

4.2. Limitations of the study

While the results are promising, several limitations should be acknowledged. First, the dataset used in this study, though diverse, was limited to 200 samples. A larger and more geographically varied dataset could improve the generalizability of the models. Second, the input features were selected based on availability and relevance, but additional parameters such as moisture content, particle size distribution, or in-situ test data might further enhance model robustness. Third, although the optimization algorithms (MGO and CHIO) significantly improved model performance, their convergence behavior and computational cost were not thoroughly analyzed, which

could affect scalability for larger datasets or real-time applications.

4.3. Potential future studies

Future research could expand on this work in several directions. Firstly, enlarging the dataset with samples from different soil types and geographic locations would enhance model generalizability and allow for regional model calibration. Secondly, incorporating more advanced machine learning models such as deep neural networks (DNNs), ensemble methods, or transfer learning approaches may yield even better predictive performance. Additionally, future studies could explore real-time or semi-real-time implementation of the proposed models in geotechnical monitoring systems. It is also recommended to investigate the comparative effectiveness of other nature-inspired optimization algorithms and assess their efficiency in terms of convergence speed, stability, and computational load.

5 Conclusion

This study tackled the complex problem of predicting undrained shear strength (USS) in soft soils near water bodies—an essential task in geotechnical engineering for ensuring structural safety and stability. The introduction contextualized the challenge posed by soft soils and highlighted the importance of USS in engineering design, along with the increasing application of machine learning (ML) techniques to enhance prediction accuracy. The research aimed to construct and evaluate data-driven models using non-linear ML approaches, particularly the K-Nearest Neighbor (KNN) algorithm and its two optimized variants: KNMG (KNN with Mountain Gazelle Optimizer) and KNCH (KNN with Coronavirus Herd Immunity Optimizer). The models were trained and tested on a dataset of 200 soil samples with four key input features—sleeve friction (SF), liquid limit (LL), plastic limit (PL), and overburden weight (OBW).

To rigorously evaluate the models, five performance metrics—R^2, RMSE, NRMSE, MSE, and Scatter Index (SI)—were used across training, validation, and test phases. The results show that the KNCH model consistently outperformed both the baseline KNN and the KNMG variant across all evaluation metrics and phases. Specifically, KNCH achieved the highest R^2 values and the lowest RMSE, MSE, NRMSE, and SI values, indicating superior accuracy and model stability. For instance, in the test phase, KNCH's RMSE was approximately 36% lower than KNMG's and 56% lower than KNN's. Its R^2 score was also 0.8% and 2% higher than those of KNMG and KNN, respectively.

While KNMG demonstrated improved performance over the baseline KNN, particularly in reducing prediction errors and increasing correlation strength, it was consistently outperformed by KNCH in every phase and metric. The baseline KNN model, although less accurate, provided a valuable benchmark for gauging the impact of optimization algorithms.

Moreover, the graphical analyses revealed that the predicted values from all three models, especially KNCH, closely followed the trends in experimentally measured USS values. This alignment underscores the effectiveness and feasibility of the proposed hybrid ML-optimization frameworks, with KNCH emerging as the most reliable model for predicting USS in soft soils.

Declarations

Availability of data and materials

Data can be shared upon request.

Competing interests

The authors declare no competing interests.

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Authors' contributions

NC performed Data collection also WY carried out simulation and LZ conducted analysis. GX evaluate the first draft of the manuscript, also JM perfomed editing and writing.

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Ethical approval

The research paper has received ethical approval from the institutional review board, ensuring the protection of participants' rights and compliance with the relevant ethical guidelines.

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Transformer-Based Fake News Classification: Evaluation of DistilBERT With CNN-LSTM and GloVe Embedding

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Social media networks have changed the face of communication in recent times, but at the same time, they have brought various challenges, such as disseminating fake news and information. NLP and machine-learning algorithms try to meet these challenges by structuring online information, although dataset bias remains a critical concern. SA has helped people gain insight into the context of news dissemination. Still, sham news dissemination-often by fake accounts represents a great hazard not only to users but to the stability of society. Several researchers have tried to assess the credibility of information and reduce sham data flow. In this work, the datasets of 17,903 fake news and 20,826 real news from Kaggle will be used. Preprocessing steps included text normalization, removal of punctuation, links, usernames, and non-alphabetic characters to prepare the data for analysis. This study explored categorizing fake and true news using advanced NLP techniques, transformer-based architectures, and deep learning models. A focus on improving classification accuracy and addressing dataset bias was achieved through models like DistilBERT, CNN, and LSTM. DistilBERT demonstrated remarkable performance, achieving an accuracy of 99.65%, with precision, recall, F1-score, and ROC-AUC values of 0.992188, 1, 0.996078, and 0.996894, respectively, outperforming the other models. The study's novelty lies in its detailed evaluation of DistilBERT, which showed significant improvements in accuracy, recall, and AUC while mitigating dataset bias. The results highlight the potential of DistilBERT for robust and reliable fake news classification, addressing critical limitations in existing approaches.

Povzetek:

1 Introduction

The advent of social media networks has revolutionized the exchange of knowledge and information, expanding reach like never before. Platforms such as Facebook, Twitter, and Instagram have facilitated communication on a global scale, allowing people to connect, share, and stay informed. However, this digital revolution has not come without its challenges. One significant consequence of the widespread use of social media is the alarming rise of false news and misinformation. The proliferation of deceptive content has led to dire consequences, impacting individuals' lives and sowing confusion among the masses [1]. As a result, there is an urgent need to address this issue and develop effective methods for identifying and combating false news. The vast volume of information published daily on online news portals and corporate websites poses a new challenge—automated organization and comprehension. To tackle this, researchers have turned to the field of NLP, specifically focusing on event extraction and classification. These approaches seek to extract and categorize crucial information about occurrences, but the unstructured nature of the initial data presents difficulties [2].

Detecting false news using ML algorithms has been a proposed solution, but most efforts have concentrated on specific types, such as political news, raising concerns about dataset bias [3]. Additionally, Sentiment Analysis, a computer-based approach that identifies emotional keywords from messages, plays a crucial role in understanding the context in which news is shared [4]. As the internet continues to expand rapidly, fake news has emerged as a pervasive societal concern, with propaganda and rumors being major culprits in misleading the public [5]. Social media, in particular, has become a primary avenue for disseminating false information through fake accounts and social bots, posing various risks to users [6]. The growth of electronic media brings both benefits and challenges. While technology grants unprecedented access to information, it also amplifies the spread of fake news, leading to conflicts and jeopardizing social stability. To combat this pressing problem, researchers are striving to evaluate the reliability of information and minimize the circulation of false data on these platforms [7].

In times of crisis, accurate detection becomes crucial for authorities to implement necessary mitigation measures. Despite the abundance of real-time data available on social media, certain studies lack efficient crisis embedding and categorization methods [8]. The pandemic illnesses such as COVID-19 have further underscored the importance of detecting false news,

necessitating robust techniques and models to combat its dissemination [9].

Given the exponential growth of social media, misinformation, especially false news (FN), has become a global issue of concern. The complexity and multimodality of fake news make it difficult to identify, demanding the use of Computational Intelligence Approaches (CIA) to automatically detect and combat its spread [10].

1.1 Related works

Several studies on the topic of Fake and Real News classification using ML and DL algorithms are covered in the following. Wani et al. (2021) used Convolutional Neural Network (CNN), Long-Short Term Memory Network (LSTM), and Bidirectional Encoder Representations from Transformers (BERT) to test supervised text classification techniques on the COVID-19 fake news identification database. Using an unlabeled Covid tweets corpus, they also evaluated the importance of independent learning, language framework pre-training, and distributed word reconstructions [1]. Dogra et al. (2021) used ML and DistilBERT, a pre-trained DL structure, to create a hybrid text categorization technique. They refined a basic model for Indian Banking news events and employed a rule-based strategy to filter out false positives and false negatives. In terms of conveying general domain knowledge, DistilBERT surpassed other ML classifiers such as LR, SVC, DT, and RF [2]. Khan et al. (2021) compared sophisticated pre-trained language models for false news detection across 3 datasets in a benchmark study. The findings of their studies showed that BERT and comparable models fared well, particularly with tiny datasets, giving them preferable possibilities for languages with minimal electronic content [3]. Karande et al. (2021) created a methodology for detecting false news early in the publication process by assessing material using automated extraction of characteristics and text relevance. They included posture as a feature and employed pre-trained contextualized word embeddings BERT to get cutting-edge results. The model beat earlier work in the real-world information set, with an accuracy of 95.32% for false news identification [7]. Liu et al. (2021) presented CrisisBERT, an end-to-end transformer-based model for 2 crisis classification tasks, namely crisis detection and crisis identification, with promising accuracy results. They demonstrated that the suggested CrisisBERT model outperforms other benchmarks in terms of resilience [8]. In the collaborative work of CLEF-2021-CheckThat! Lab, Balouchzahi, Shashirekha, and Sidorov (2021) created models for identifying bogus news. They used training data to fine-tune 3 transformer-based language models from HuggingFace, Roberta, Distilbert, and BERT, then assembled them as estimators using majority voting. The algorithms are text classification problems with several classes [9]. Ogundokun et al. (2022) suggested a computational intelligence-based false news detection method that reduces vector-based feature dimensions employing a dimensionality reduction technique. They used 3 different CIAs: the GA, the K-Nearest Neighbor (KNN), and the BEL. Using confusion matrix metrics, the system's performance was analyzed, and it was discovered that GA with KNN surpassed GA with BEL in accuracy, sensitivity, and precision [10]. Fine-tuned multipurpose language representation models, for example, the BERT group framework (BERT, Distil-BERT), and the word embedding-based CNN and Fast-Text models, were employed by Saha et al. (2022) to successfully carry out the research. In this investigation, Distil-BERT outperformed BERT, Fast-Text, and CNNB accuracy [4]. Abdullah, Altiti, and Obiedat (2022) employed RoBERTa, a pre-trained language model, to identify complicated propaganda strategies in online news stories. The model was assessed utilizing a reference dataset for SemEval-2020 Task 11 [5]. Verma et al. (2022) present a User Credibility (UCred) model for distinguishing between false and legitimate user accounts. To categorize profiles, the model employs RoBERT, Bi-LSTM, and RF methods. The result is input into a voting classifier, which improves accuracy above state-of-the-art methods [6].

Kaliyar et al. (2021) addressed the issue of faking news in today's news era, with social networks allowing rapid and widespread dissemination of information, at times including untrue information. Previous work utilized sequential neural networks to model news content and social contextual information, but such work processed sequences of text in a unidirectional approach, limiting them to modeling semantic and long-range dependencies in a sequence. To address this problem, in this work, the authors designed FakeBERT, a deep neural model, combining Bidirectional Encoder Representations from Transformers (BERT) with parallel single-layer Convolutional Neural Networks (CNNs) with a variety of dimensions and filters of the kernel. FakeBERT was designed to enhance classification accuracy through use of bidirectional training to model semantic dependencies and mitigate uncertainty in natural language processing. Experimental performance revealed that FakeBERT performed much better than current models, with accuracy at 98.90%. In this work, the authors introduce a successful integration of models of BERT and CNN to address the issue of faking news, offering a strong model for enhancing natural language processing in such an issue [11]. Khanam et al. (2021) addressed the increasingly common issue of social and national destructive disinformation through spurious news in social networks and general platforms, citing its possible widespread social and national destructive impact. In a move to adequately counter such an issue, the authors conducted current studies in identifying spurious news and focused specifically on choosing the most effective conventional machine learning algorithms for real and spurious news differentiation. In a process that involved utilizing supervised machine learning algorithms, tools such as Python's scikit-learn package and natural language processing (NLP) for text processing, the developed model utilized tokenization and feature extraction with tools such as Count Vectorizer and Tfidf Vectorizer,

culminating in feature selection, with experiments for feature selection and maximization of precision, measured in terms of output through a confusion matrix. The work shed new insights in terms of using conventional machine learning techniques and feature engineering in enhancing spurious news detection, with an emphasis placed in terms of using efficiency in curbing the widespread circulation of counterfeit information [12].

Bangyal et al. (2021) leveraged deep and machine algorithms for Twitter COVID-19 fake news sentiment analysis and achieved high accuracy using TF-IDF representation and algorithms including CNN and LSTM. In their work, recommendations for successful social network sentiment classification were proposed [13]. Alsuwat and Alsuwat (2025) addressed the growing issue of disinformation and misinformation, particularly via social media, with a proposed Framework for a Multi-Modal Fake News Detection (MM-FND). Having acknowledged the vulnerability of current methods, utilizing a single narrow feature set, the authors proposed combining several types of data for detection accuracytection. With three datasets, ISOT Fake News Dataset, LIAR Dataset, and COVID-19 Fake News Dataset, developed in their proposed framework, global feature extraction involved Word2Vec and Term Frequency-Inverse Document Frequency (TF-IDF), temporal feature through Bidirectional Long Short-Term Memory (Bi-LSTM) networks, and spatial feature through Named Entity Recognition (NER) and Global Vectors for Word Representation (GloVe). Classifier for classification involved Random Forest, leveraging the complementary strengths of these feature extraction methodologies. The proposed MM-FND framework performed better than conventional methods in terms of accuracy in detection. It achieved 96.3% (F1: 96.4%) for ISOT, 95.6% (F1: 94.2%) for LIAR, and 97.1% (F1: 97.9%) for the COVID-19 datasets. Findings displayed the effectiveness and robustness of the proposed framework in disinformation identification in a range of datasets, offering an effective tool in countering social and individual loss incurred through disinformation [14].

Altamimi (2024) proposed a model combining FastText, FastText-Subword, and GloVe embeddings with a custom-designed CNN for detecting fake news. With 94.58 accuracy and outclassing existing models, it showed prowess over datasets, including an independent Arabic Fake News dataset, offering a general-purpose model for countering disinformation [15]. Ellaky et al. (2024) designed a hybrid model combining GloVe embeddings with BiGRU and LSTM for social bot detection. With 100% precision and 99.73% accuracy for the Twibot-20 dataset, the model outclassed current methods and performed accurately in bot detection in new samples, illuminating deep learning's potential in bot detection [16].

Abdal et al. (2023) addressed the social threat of the mass proliferation of spurious information, citing an urgency for multilinguality detection frameworks in an aim to preserve an educated information environment. Abdal et al., in their work, proposed a transformer model for detecting Bangla fake information using a distilled model of the BERT model, namely, DistilBERT. Abdal et al. prepared a large corpus of samples of real and spurious samples of Bangla information for training and fine-tuning for model development. Through contextual and semantic awareness, Abdal et al. trained the model using a large corpus of Bangla information corpus. For evaluation, Abdal et al. compared a model using DistilBERT with traditional machine algorithms such as SVM and RF, and deep training algorithms such as LSTM. Experimental results confirmed that a proposed model outperformed alternatives with accuracy in detection of 97.85% in spurious information for Bangla language. This work attests to the effectiveness of transformer-based models in multilinguality in the detection of fabricated information and offers a powerful tool in curbing disinformation in language Bangla [17]. Kula et al. (2021) discussed model development and model evaluation for detecting fake news, particularly in relation to the most important social issue posed by disinformation in the new era of telecommunications. In developing the model, current state-of-the-art neural network architectures of the Transformers family were utilized, utilizing high-performance computation capabilities through Google Colaboratory platform and Flair library capabilities. Precision, recall, and an F1-score were utilized for model quality evaluation, providing a robust analysis of model performance. In its analysis, the work documented an assurance of strong artificial intelligence and deep learning approaches in the battle against fake news, with such tools proven capable of providing effective and reliable countermeasures against disinformation. With high-tech tools, developed models in this work showed a high-potential contribution towards countering the spread of fake news and enhancing social resistance to disinformation [18].

Chabukswar et al. (2024) debated about the social peril of disinformation, highlighting the urgency of discovering counterfeit news in all languages to have an educated and dependable information environment. The work suggested a transformer-based pre-trained model combining Distilled Bidirectional Encoder Representations from Transformers (DistilBERT) and Bidirectional Gated Recurrent Units (BiGRU) for identifying fake news in the English language. To that, a careful collection of political news articles, real and fabricated, was prepared. NLTK was utilized for the preprocessing of text, and a fine-tuning of the DistilBERT model for semantic relations and contextual information in the English language was performed. Model output underwent BiGRU layers, and sequential information and adjacent token dependences were extracted and captured. Experimental evaluation confirmed that the model performed effectively, and a high accuracy rating of 97.26% in discovering English fake news was attained. In the current work, it is displayed that integration of transformer-based architectures with recurrent layers can maximize accuracy in discovering fake news in English-language collections [19]. Zhi et al. (2021) tackled the biggest problem of financial fake news, one that can sway

public opinion and manipulate financial markets. Confronted with the weakness of purely feature-based language models, authors proposed an overall scheme through integration of multi-source fact-checking and analysis with fake news detection. With a range of dimensions such as user comments, information sources, and financial market information, in terms of enhancing accuracy in detection, their multi-fact CNN-LSTM model operated. User comments were leveraged with an attention mechanism for useful information extraction, and a well-prepared white-list of high-quality web sources was adopted for information source checking. Information about financial products in the news, including financial markets, was checked, and statements were checked with real-time actual market price statements. Dynamical weighting during training allowed the model to assign weight to each dimension and dynamically learn them during training. Unlike purely model-based approaches, such an overall scheme effectively addressed complex financial fake news, and its successful establishment emphasized the importance of leveraging several sources of information for developing strong detection systems [20].

Several studies have explored fake and real news classification using machine learning (ML) and deep learning (DL) algorithms. Table 1 provides a summary of methodologies, datasets, reported accuracies, and limitations from prior works.

Table 1: Summary of previous studies on fake news classification

Study	Methodology	Dataset	Accuracy	Limitations
Wani et al. (2021)	CNN, LSTM, BERT	COVID-19 Fake News Dataset	~95%	Limited generalizability to non-COVID datasets; lacks contextual depth in text.
Dogra et al. (2021)	DistilBERT, Rule-Based Filtering	Indian Banking News Dataset	~96%	Dataset-specific, not scalable to broader topics of fake news.
Khan et al. (2021)	BERT Variants	Multiple Small Datasets	~94%	Limited to small datasets; computational inefficiency with large models.
Karande et al. (2021)	BERT, Feature Extraction	Social Media Posts	95.32%	High computational cost for real-time applications.
Liu et al. (2021)	CrisisBERT	Crisis News Dataset	~92%	Focused only on crisis-related news; lacks general applicability.
Ogundokun et al. (2022)	CI Techniques (KNN, BEL, GA)	Social Media Data	~89%	High dimensionality and reduced scalability.
Abdullah et al. (2022)	RoBERTa, Propaganda Classification	SemEval-2020 Task 11 Dataset	~93%	Limited to specific propaganda detection; not generalizable to other tasks.
Saha et al. (2022)	DistilBERT, FastText, CNN	Public Sentiment Dataset	~94%	Focused on sentiment analysis rather than fake news classification.
Kaliyar et al. (2021)	FakeBERT combining BERT with parallel single-layer CNNs to enhance semantic dependency modeling.	Custom Dataset	98.90%	Demonstrated improved performance through bidirectional training and semantic dependency modeling.
Khanam et al. (2021)	Supervised ML with tokenization, feature extraction, and confusion matrix-based precision evaluation.	Custom Dataset	Not specified	Highlighted efficient spurious news detection through conventional ML and feature engineering.
Bangyal et al. (2021)	TF-IDF representation with CNN and LSTM for Twitter COVID-19 fake news sentiment analysis.	Twitter COVID-19 Dataset	High accuracy	Proposed social network sentiment classification techniques.
Alsuwat & Alsuwat (2025)	Multi-Modal Fake News Detection (MM-FND) using Word2Vec, TF-IDF, Bi-LSTM, and NER.	ISOT, LIAR, COVID-19 Datasets	96.3%-97.1%	Robust multi-modal approach leveraging complementary feature extraction methodologies.
Altamimi (2024)	Custom CNN with FastText, FastText-Subword, and GloVe embeddings.	Arabic Fake News Dataset	94.58%	Showcased a general-purpose model for countering

				disinformation, particularly in Arabic datasets.
Ellaky et al. (2024)	Hybrid model combining GloVe with BiGRU and LSTM for social bot detection.	Twibot-20 Dataset	99.73%	Highlighted the potential of deep learning for accurate bot detection.
Abdal et al. (2023)	DistilBERT model for Bangla fake news detection with contextual and semantic awareness.	Bangla Fake News Corpus	97.85%	Demonstrated transformer models' effectiveness in multilingual fake news detection.
Kula et al. (2021)	Transformer architectures evaluated using Google Colab and Flair library for model quality.	Not specified	High accuracy	Showed strong potential for using advanced AI tools to counter disinformation effectively.
Chabukswar et al. (2024)	Transformer-based DistilBERT fine-tuned with BiGRU for fake news detection in English.	Political News Corpus	97.26%	Demonstrated the integration of transformer-based architectures with recurrent layers for enhanced accuracy.
Zhi et al. (2021)	Multi-source fact-checking and detection model with CNN-LSTM leveraging user comments, sources, and market data.	Financial News Dataset	Not specified	Highlighted the importance of leveraging multi-source information to tackle complex financial fake news.

The state-of-the-art models, BERT, RoBERTa, and their derivatives like DistilBERT, have shown promising accuracy in text classification tasks, such as fake news detection. Most of them, however, suffer from certain inadequacies: large transformer models, for example, like BERT, require huge computational power and, therefore, are not suited for real-time applications. Most of the previous studies conducted had focused on datasets that were either from a specific domain or highly unbalanced, such as COVID-19-related news; hence, biased and less applicable. Furthermore, most of the models are optimized to perform well on only one dataset or a particular topic, while they perform badly on others. Lastly, even if a model is accurate, transformer-based models would tend to behave like black boxes, hence making the decision process uninterpretable. To resolve those issues, this paper uses DistilBERT, the distilled version of BERT, since it has the goal of balancing its high performance with computational overhead. It is also applied to the Kaggle Fake and True News dataset to include more fake and true news items to increase the generalizability of the findings. It further systemically compares DistilBERT against CNN-LSTM models with better results in terms of accuracy, recall, and AUC score. Further, it has applied preprocessing techniques and balanced evaluation metrics to reduce the bias of the dataset. In light of this approach, one can see how DistilBERT achieves state-of-the-art performance by dealing with computational inefficiencies and biases, hence contributing to more robust and reliable fake news classification.

Given these challenges, it is clear that solving the issue of distinguishing between fake and true news necessitates a rigorous method of classification on time following the publication of news. Furthermore, earlier proposed approaches have limited accuracy or are incomplete. However, the research has failed to give the reasons why these models were chosen; nor has it supported the selection in the light of fake news classification. Here, a suitable explanation for employing these models-based on their appropriateness can be CNN because of its feature extraction ability, CNN-LSTM for its ability to process sequential data, and DistilBERT because of its efficiency in transformer models. This will explain their suitability for solving the problems of fake news detection. Another thing is that the study has not mentioned the reasons for not using other deep models, such as RoBERTa, XLNet, or even GPT-based architecture, which proved to have promising performances in similar tasks and could give so much insight into this research. Adding in a performance comparison of these options would have made the onus of the study design show that these selected models were the best for this use.

The lack of justification further opens up gaps in understanding the criteria behind the choice of models, leaving one speculating whether the results could have been further improved by other approaches. This shall enhance the transparency and robustness of the methodology in establishing that the study makes a valid contribution within the domain of misinformation detection.

This study's subsequent portion is arranged as follows: Section 2 focuses on technique in many subsections, including dataset analysis, methodology, and performance evaluation. The third component of this study contrasted base and classification approaches, while section 4 highlighted the study's key findings.

2 Methods

Fig. 1 shows the flowchart of the research methodology. The dataset was chosen from the Kaggle Fake and True data sets. The preprocessing and word embedding processes were then applied to input datasets for use in

classification models. DL models and the Distilbert transformer model, its own parameters structure the models are discussed further below. Finally, the best model was chosen based on performance.

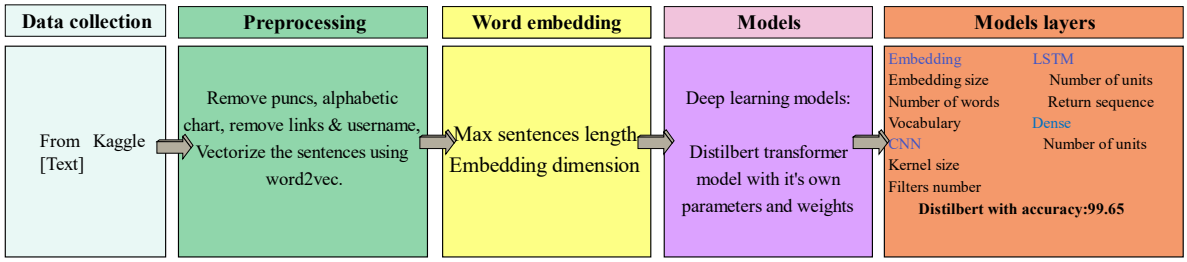


Figure 1: The flowchart diagram of this study

2.1 Research design

This study, therefore, adopted a research design to test the efficiency of different deep learning models for classification, but mainly compared performances between DistilBERT and CNN-LSTM models. The main objective of this research was testing the performance of these two models against their accuracy, recall, and overall performances in classification on a diverse dataset and also to check if DistilBERT eliminates those existing drawbacks that were revealed in other state-of-the-art models regarding inefficiency in computation and generalization issues. Hence, the hypothesis which was tested is that DistilBERT, relying on its transformer-based architecture and potentiality of fine-tuning, will outperform CNN-LSTM in terms of accuracy, recall, and robustness against biases of datasets. Therefore, the following are the research questions that this study attempted to answer:

1. How does DistilBERT's performance compare to the performance of CNN-LSTM models in fake news classification?
2. What are the most influencing factors that create the distinction between these ensembles?
3. Can DistilBERT alleviate both the computational inefficiency and poor generalizability of the traditional methods?

The proposed experiment design is targeted at modeling comparisons fairly and systematically. The reason for choosing the Kaggle Fake and True News dataset was the presence of a comprehensive and diverse collection of both fake and true news articles, which makes it suitable for testing generalizability across a variety of domains. Normalization of text, punctuation removal, and GloVe vectorization of text have been used consistently for all models to avoid any discrepancy. DistilBERT was chosen due to its reduced computational cost, along with its effectiveness in text classification tasks. CNN-LSTM models were chosen to represent a range of hybrid deep learning architectures that integrate convolution and sequence-based processing. Several CNN-LSTM variants, such as 2- and 3-layered models, have been utilized to present a detailed analysis of performance variation due to the shifting complexity in architecture.

These are the three intended outcomes of the study. Firstly, this research shall determine the best model performing the fake news classification based on Accuracy, Recall, and AUC. Secondly, this aims at proving the applicability of transformer-based models, such as DistilBERT, in real-world cases, embedding fake news detectors into social media. Finally, this research tries to bring to light the difficulties and limits of the existing methods, such as the dataset being biased or the computational inefficiency by giving ways for overcoming them. Thus, the research will hopefully develop further in constructing more robust, efficient, and generalizable models against misinformation in digital media.

2.2 Dataset

The "Fake" and "True" datasets from Kaggle were used in this work to identify fake news items. This data set contains 17,903 and 20826 distinct false and true news values, respectively.

2.2.1 Preprocessing steps

Preprocessing steps included:

1. Text normalization, such as converting text to lowercase.
2. Removal of punctuation, links, usernames, and non-alphabetic characters to clean the dataset.
3. Stratified sampling to address the slight class imbalance (53.8% true news vs. 46.2% fake news).

Also, the training of the presented deep learning model is conducted with a batch size of 32, and the Adam optimizer is employed to ensure impactful gradient optimization. The learning rate is set to 10^{-4} for the deep learning models, while a smaller learning rate of 10^{-5} is adopted for DistilBERT, as it is a larger model and needs fine-tuning to achieve optimal outputs. The input sentence length is fixed at 1500 tokens to maintain consistency in data processing. Training and fine-tuning are performed over 200 epochs to guarantee sufficient learning and convergence for the deep learning models and DistilBERT.

2.2.2 Impact of preprocessing

The preprocessing processes helped in a significant improvement in model performance and less bias in the

dataset. Text processing such as converting to lowercase and removal of punctuation, links, username, and non-alphanumeric characters helped in excluding irrelevant factors interfering with the model's ability for meaningful patterns to learn. Stratified sampling helped in counterbalancing minor unbalanced datasets (53.8% for real and 46.2% for fake news) and offering balanced training representation for both datasets. All these processes together cleaned out noise in the dataset and helped in models such as CNN-LSTM and DistilBERT in focusing on intrinsic factors of a text. Embedding selection (static GloVe-300 for CNN-LSTM and dynamically generated DistilBERT embedding) added to these preprocessing processes, in addition to a further boost in capability of models for distinguishing between fake and real news in terms of contextual and semantic accuracy

This study employed GloVe-300-word embeddings for certain models to enhance text representation and enable comparisons with transformer-based embeddings used in DistilBERT. GloVe-300 embeddings, known for their ability to capture semantic relationships between words, were specifically used with CNN-LSTM models as part of this study's comparative analysis. The choice of GloVe-300 was motivated by its widespread application in deep learning for natural language processing tasks, particularly in scenarios requiring static word embeddings. The transformer model DistilBERT was compared with CNN-LSTM, 2CNN-LSTM, and 3CNN-LSTM.

Figs. 2 and 3 show word clouds from the Fake and True datasets separately. Thus, in these figures, more common subjects in news articles were shown in large font, while less repeated topics were shown in small font.

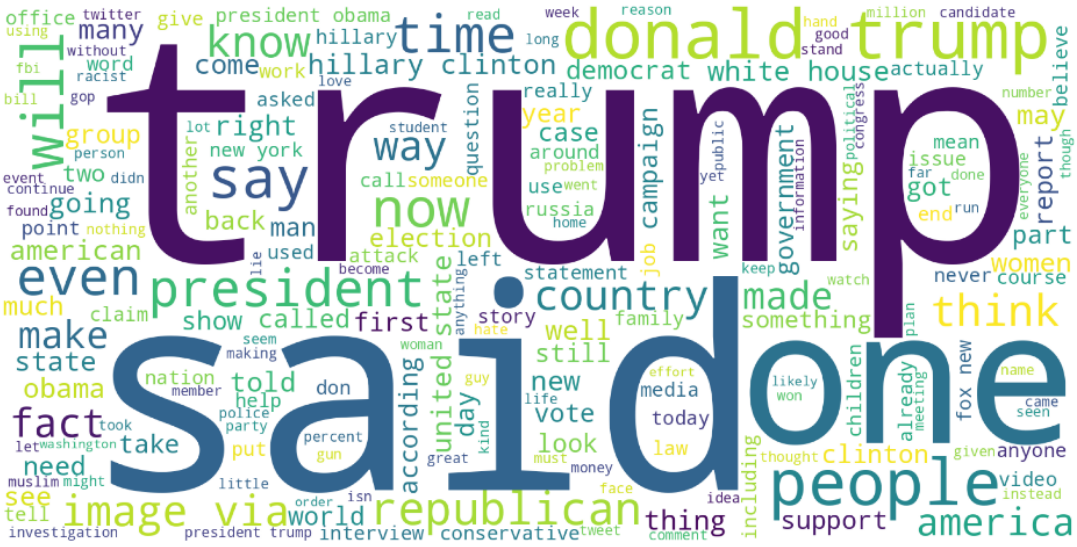


Figure 2: The word clouds of Fake class

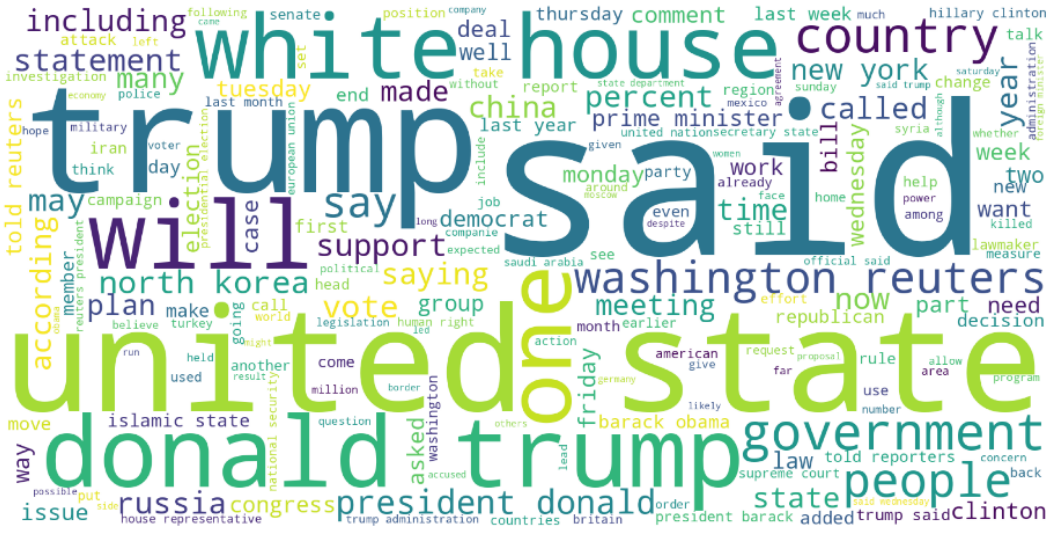


Figure 3: The word clouds of True or real class

Figure 4 illustrates sentence length analysis over the dataset for four possible thresholds: 1000, 1300, 1500, and 2000 words. Herein, it was determined that 1500, in sentence length one (yellow line), encodes 99.35% of the input dataset, including just about all sentences without adding too much padding or cutting off. This is chosen

because the threshold brings a good balance between computational efficiency and useful content retention in the dataset, hence being appropriate for downstream text classification tasks.

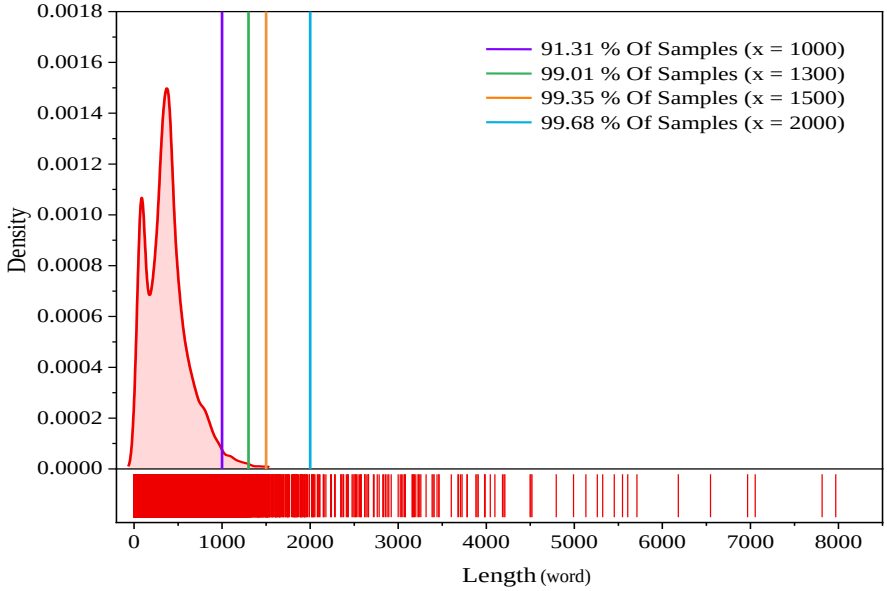


Figure 4: Histogram and line cover of input datasets

Fig. 5 displays the distribution of True and Fake news in the dataset, where 53.8% of the articles are classified as True news and 46.2% as Fake news. This slight imbalance, where True news is more prevalent, maybe a result of the dataset's composition on Kaggle, which could include more True news for validation purposes or to ensure a higher degree of authenticity in the data. While this imbalance is not extreme, it can still have implications for model performance. Specifically, the model might be biased toward predicting the majority class (True news), potentially leading to lower recall for Fake news. Such an imbalance can also inflate accuracy metrics, as models that predict the majority class more often will naturally perform better. To mitigate these effects, preprocessing techniques such as stratified sampling or class weighting were applied during model training. Moreover, evaluation metrics like F1-score and ROC-AUC, which are more sensitive to class imbalance, were chosen to ensure a fair assessment of the model's performance for both classes. This discussion emphasizes the importance of considering class distribution when evaluating fake news classification models.

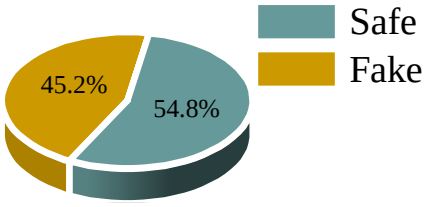


Figure 5: Pie chart of fake and true percentages

In this study, preprocessing entails lowering the text, eliminating punctuation, removing links and user names, and removing non-alphabetic letters. Texts were also converted to vectors using word2vec. The sentences were inflated to the length of the longest sentence, 64. Word2vec was utilized to vectorize the text phrases, enabling the use of word embeddings.

The GloVe-300 embeddings used in this study were only for the CNN-LSTM models. It is such embeddings that are provided to the CNN-LSTM architectures for initializing the word vectors with pre-trained word embeddings on large text corpora. Such embeddings were contrasted against an embedding matrix that has been trained on the dataset used in this study for fairness.

In contrast, the DistilBERT model used its own pre-trained transformer-based token embeddings, which capture the meaning of the word dynamically depending on the context. For DistilBERT, no static embeddings such as GloVe-300 were used, keeping in line with its transformer-based architecture. This is important for comparing the various performances of models using static embeddings, CNN-LSTM, and dynamic embeddings, DistilBERT.

To catch 99.35% of samples, consider a vocabulary size of 15000 words and a sentence length of 1500.

2.3 Convolutional neural network

Unlike other approaches, the Convolutional Neural Network (CNN) [21] comprises a feedforward neural network that identifies characteristics from the input using convolution architectures. Its design was driven by the sense of sight, with neurons from nature equating to synthetic versions and CNN kernels mimicking receptors. Activation functions replicate neural communication of signals, whereas loss functions and optimizers instruct the CNN system to acquire anticipated [22]. CNN structures are divided into 3 categories: convolutional, pooling, and fully connected layers. Pooling layers calculate distinct mappings of features, while convolutional layers learn representations of characteristics from data inputs. Each neuron in the preceding layer is linked to an area of nearby

neurons. Convolving the input with a learned kernel and using an element-wise nonlinear function of activation yields a novel feature list. Several kernels are used to generate comprehensive maps of characteristics [23]. The basic elements of CNN are provided here to aid in better understanding.

2.3.1 Layers of convolutions

A convolution layer, which combines linear and nonlinear processes such as convolution and activation functions, is an important CNN layer for finding features. Convolution is a linear discovery of features procedure that applies a kernel to a tensor. At every point, the element-wise product of the kernel and the input tensor is computed, yielding the characteristic mapping. This method is repeated to generate numerous maps of characteristics reflecting distinct input tensor properties, resulting in diverse characteristic extractors [24]. A convolutional layer is a series of parallel characteristics produced by sliding various kernels. It conducts product and summation between the kernel and the input picture, translating data into feature maps. The kernel is smaller than the source picture [25].

2.3.2 Layers of pooling

Pooling is a key principle in CNNs since it reduces computational load by minimizing links between layers of convolution. Recent pooling approaches, such as max-pooling, minimize image processing complications and resolution. It divides photos into rectangular sub-regions and returns the greatest value inside each sub-region [23,26].

2.3.3 Activation function

Non-linearity is the subsequent layer following convolution, and it modifies or restricts the result of the algorithm. The activation function is utilized to activate neuronal properties while also preserving and mapping features. It specifies the output of a specific neuron following a sequence of inputs, maintaining characteristics and reducing data redundancy. The activation function is a function between 2 layers in multilayer neural networks. CNNs, like the neuron model in the human brain, may represent complex properties by using multiple activation functions. Each neuron receives the previous layer's output value as input and transfers the processed data to its subsequent layer [22,26,27]. Several common activation functions, in the following, are described.

- Rectified linear unit (RELU) functions as a well-known non-saturated function for activation. Mathematically, the RELU is stated as follows:

$$ReLU(x) = \max(0, x)$$
$$\frac{d}{dx} ReLU(x) = \{1\ if\ x > 0; 0\ otherwise\} \quad (1)$$

$ReLU$ acts as a piecewise linear function that eliminates negative sections while keeping positive ones. It produces sparsity in hidden units and is quicker than other activation functions. Despite the discontinuity at 0 that might impact backpropagation performance, experimentally, ReLU surpasses other activation functions.

- The SoftMax function is a scalar-valued function that has an exponential assessed at each vector component and is normalized by the sum of every one of the scalar components [28]. Regardless of the use, its look differs. The SoftMax function $SM: \mathbb{R}^k \rightarrow \mathbb{R}^k$ is stated below:

$$SM(Z)_j = \frac{e^{Z_j}}{\sum_{i=1}^{k} e^{Z_i}} \quad (2)$$

Every component Z_j in the input vector Z, is subjected to the exponential function, and the outcomes are normalized by division by the total sum of the exponentials. This guarantees that the resulting vector $SM(Z)$ sums to one [29].

2.3.4 Layer of fully connected dense

The dense layer is fully linked and serves as a classifier. Whereas convolutional layers, pooling layers, and activation function layers map the initial data to hidden characteristics, the fully connected layer maps learned characteristics into the sample markup area [25].

2.3.5 Loss function

A loss function, formerly referred to as a cost function, assesses the similarity of network forecasts of results and reality labels. The cross-entropy approach is often employed for the classification of multiple classes. Loss functions are hyperparameters that have been developed for particular duties and are used as training criteria in optimization and regression situations.

2.3.6 Embedding

The GloVe (Global Vectors for Word Representation) model was used to generate word embeddings for the CNN-LSTM models in this study. GloVe learns word representations by analyzing the co-occurrence statistics of words within a large corpus. Specifically, it reduces the dimensions of the co-occurrence matrix to create dense vector representations of words, where similar words have similar vector representations. This process captures both semantic relationships and contextual similarities, enabling the model to represent textual data effectively [30]. Glove learns word embeddings by lowering the number of dimensions of the co-occurrence number matrix and utilizing proportions of co-occurrence probability to discriminate important from extraneous words. By training on nonzero entries in a word-word cooccurrence matrix, this model successfully employs data from statistics, yielding an important vector area [31].

For this study, GloVe-300 embeddings, pre-trained on a large corpus, were chosen to initialize the embedding layer in CNN-LSTM models. These embeddings provide a static representation of words, which is well-suited for

the sequential processing capabilities of CNN-LSTM architectures. By using GloVe, the models can leverage pre-existing knowledge about word relationships, improving their ability to classify fake and true news articles.

However, static embeddings like GloVe have limitations, such as the inability to account for word meanings in different contexts (e.g., "bank" as a financial institution vs. "bank" as a riverbank). This contrasts with the transformer-based embeddings in DistilBERT, which dynamically adjust word meanings based on context. Despite this, GloVe was selected for CNN-LSTM models due to its efficiency and compatibility with the architecture, providing a strong baseline for comparison with transformer-based models

2.4 Long short-term memory

The long short-term memory (LSTM) approach, initially introduced by Hochreiter and Schmid Huber in 1997 [32], is a popular deep-learning technique for digesting and forecasting significant occurrences in time series with large intervals. Because of its lengthy data processing capabilities, it is especially effective for handling information with long-term dependencies, where the outcome is dependent on earlier time steps [33–35]. There are 3 gates in an LSTM memory cell: forget, input, and output. During training, each gate gets assigned a distinct duty. The cell state stores the alteration in the state, ensuring that earlier data is preserved. The forget gate determines persistence by testing the relevance of data from the prior state via a sigmoid function. The input gate provides new data, while the output gate determines forecasts from the current time step's modified state and input [36]. An LSTM network consists of the following components:

The input gate determines how much network information is required for internal storage as well as information flow to memory cells.

$$I_t = \sigma(W_{ih}h_{t-1} + W_{ix}x_t + b_i) \quad (3)$$

Here σ refers to the logistic function, h_{t-1}, and x_t demonstrate the memory cell target and the input vector, respectively; W_{ih}, W_{ix} denotes the weight matrix of the input gate, and b_i indicates the term that defines the bias of the input gate.

The forget gate regulates data flow and removes previous data in memory cells.

$$F_t = \sigma(W_{fh}h_{t-1} + W_{fx}x_t + b_f) \quad (4)$$

Memory cell output to the network is controlled by the output gate, which determines the internal state data required for external state output.

$$O_t = \sigma(W_{oh}h_{t-1} + W_{ox}x_t + b_o) \quad (5)$$

In memory cells, the cell state maintains the information.

$$C_t = f_t C_{t-1} + \tanh(W_{ch}h_{t-1} + W_{cx}x_t + b_c) \quad (6)$$

In the hidden state, the LSTM unit outputs forecasts or data to the following unit.

$$S_t = O_t + \tanh(C_t) \quad (7)$$

2.5 DistilBERT

DistilBERT is a simplified variant of BERT that was introduced by [37] that employs the distillation of information, does away with token-type embeddings and the pooler, and reduces layers by an amount of 2 [38]. DistilBERT is a knowledge distillation-based ML algorithm assessment method that includes moving data from the primary model, the teacher, to a lesser, distilled version, the student. This compression technique explains how a model generalizes and transfers knowledge from instructor to student. DistilBERT uses the same procedures as the original BERT to design a student version and teach it on a bespoke dataset for a given purpose, involving pre-training and fine-tuning [39]. The DistilBERT student structure is similar to BERT, however, it eliminates token-type embeddings and the pooler, as well as reduces the number of layers through an amount of 2. In recent algebraic frameworks, the majority of operations in Transformer construction, including linear layer and layer normalization, are significantly optimized. Variations in the hidden size dimension have a lesser influence on computing efficiency for constant variable budgets than variables such as the number of layers, according to research. As a result, the emphasis is on minimizing the number of layers [37]. Student initialization plays an important role in training processes that make use of the shared dimensionality of teacher and student systems. In removing just one of the 2 layers, the sub-network converges, improving the training method. Distil BERT has been trained on huge batches using excellent approaches, such as gradient accumulation and dynamic masking, despite the next sentence forecasting aim.

2.6 Architectures of models

The article's performance of the models was assessed in this section. In the whole model, training was done on GPU. The architects of models are expressed as follows.
In the Distilbert transformer model that was used pre-trained model. The Distilbert model was employed as the suggested model's backbone and as the final layers. And one Dense layer with 64 units activated by RELU. In addition, there is one thick layer with one unit and an activation sigmoid for classification.

3-LSTM models involve embedding layer with 300 dimensions, LSTM with 64 units with return_sequens=True (in a bidirectional way), LSTM with 128 units with return Sequens=True (in a bidirectional way), LSTM with 256 units (in a bidirectional way), Dense layer with 64 units with RELU activation, and Dense layer with 1 unit for classification with sigmoid activation.

In the CNN-LSTM model with Embedding layer with 300 dimensions, a one-dimensional CNN layer (CNN1d) with kernel size 32 filters and 2 for kernel size with RELU activation, LSTM with 32 units (in a bidirectional way), Dense layer with 64 units with RELU activation, and Dense layer with 1 unit for classification with sigmoid activation was trained.

While included in the 2CNN-LSTM model are the Embedding layer with 300 dimensions, CNN1d with kernel size 32 filters and 2 for kernel size with RELU activation, CNN1d with kernel size 64 filters and 2 for kernel size with RELU activation, LSTM with 32 units with return_sequens=True (in a bidirectional way), LSTM with 64 units (in a bidirectional way), Dense layer with 64 units with RELU activation, and Dense layer with 1 unit for classification with sigmoid activation.

3CNN-LSTM model architects use Embedding layer with 300 dimensions, CNN1d with kernel size 32 filters and 2 for kernel size with RELU activation, CNN1d with kernel size 64 filters and 2 for kernel size with RELU activation, CNN1d with kernel size 128 filters and 2 for kernel size with RELU activation, LSTM with 32 units with return_sequens=True (in a bidirectional way), LSTM with 64 units with return Sequens=True (in bidirectional way), LSTM with 128 units (in a bidirectional way), Dense layer with 64 units with RELU activation, and Dense layer with 2 units for classification with sigmoid activation.

2.7 Evaluation of the performance

A confusion matrix is a table that is used to characterize and evaluate the efficiency of a classification method, effectively analyzing classification challenges. It visualizes and summarizes the performance of the method, using row and column numbers corresponding to class numbers. The confusion matrix is made up of 4 main properties which are utilized to create the classifier's measuring criteria [40]. These 4 figures are:

- TP stands true positive. The method's anticipated worth matches false news, indicating accurate categorization and false news propagating through social networks.
- FN represents a false negative. Its output happens when legitimate news is wrongly labeled as negative.
- TN (True negative) indicates that the system successfully identified a news item whenever its anticipated value fits what is happening.
- FP (False positive): News is mistakenly categorized as legitimate news even when it's fake news [41].

The confusion matrix was utilized for assessing the performance of data classification techniques utilizing criteria such as accuracy, error, precision, recall, F1-score, and AUC, which is expressed as follows:

Accuracy

The accuracy criteria are used to assess the model's correct diagnosis. The proportion of correct diagnoses to total data is used to calculate accuracy for the balanced dataset.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

Precision

The precision factors signify the ratio of the number of specimens with a correct positive diagnosis to the overall number of positive diagnoses.

$$Pre = \frac{TP}{TP + FP} \quad (9)$$

Recall

The recall metric is given as the percentage of accurate positive results out of the overall number of specimens that have to be positive.

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

F1 score

The F1 score represents the balance of accuracy and recall.

$$F1 = \frac{2 \cdot Pre \cdot Recall}{Pre + Recall} \quad (11)$$

AUC

AUC measures the accuracy of model predictions independent of the categorization criterion. AUC may be critical in lowering classification errors in circumstances with dramatically differing false negatives and false positives costs, such as emphasizing reduced false positives despite a considerable rise in false negatives.

2.8 Reason for model choice

The research utilized DistilBERT for its performance and computational efficiency and leveraged its use of a distilled model in minimizing computational requirements. CNN-LSTM models were utilized as examples of hybrid architectures with capabilities in feature extraction (with CNN) and sequence modeling (with LSTM). Nevertheless, lighter transformer alternatives such as RoBERTa or XLNet were not included, a limitation for future studies to capitalize on.

3 Results and discussion

In this section of the paper, the performance of the Distilbert models and 3-LSTM, CNN-LSTM, 2CNN-LSTM, and 3CNN-LSTM methods are compared to each other to classify Fake and True news. The compared criteria involved accuracy, precision, recall, F1-score, and AUC of the prediction models. Then, the best prediction model is chosen according to the performance of the criteria.

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Fig. 6 depicts the accuracy, precision, recall, F1-score, and AUC criteria of models, with further information in Table 2. 3CNN-LSTM is the weakest model based on classification model criterion values. The performance of the 2CNN-LSTM, CNN-LSTM, and 3-LSTM ranges from poor to excellent. The Distilbert transformer model is the most resilient and best model

based on all criteria. Although all of the models utilized in this study are appropriate for classifying Fake and True news, the Distilbert model has the potential for substantial accuracy and performance.

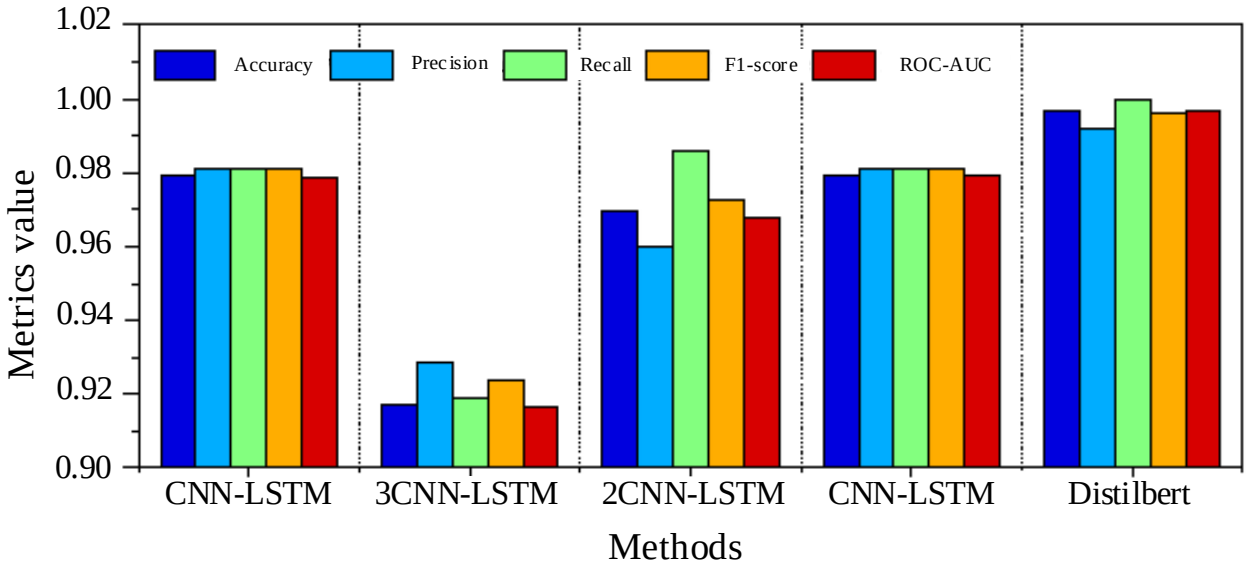


Figure 6: Metrics value for Distilbert, 3-LSTM, CNN-LSTM, 2CNN-LSTM, and 3CNN-LSTM methods

Table 2: Criteria values of Distilbert, 3-LSTM, CNN-LSTM, 2CNN-LSTM, and 3CNN-LSTM methods

Models	Accuracy	Precision	Recall	F1	ROC-AUC
3-LSTM	0.980207	0.971984	0.992435	0.982103	0.978932
3CNN-LSTM	0.917076	0.928588	0.919149	0.923845	0.91686
2CNN-LSTM	0.969599	0.959724	0.985816	0.972595	0.967908
CNN-LSTM	0.979301	0.981315	0.980851	0.981083	0.97914
Distilbert	0.996528	0.992188	1	0.996078	0.996894
Naive Bayes	0.830207	0.811984	0.842435	0.8269	0.838932

The comparative analysis revealed that DistilBERT achieved the highest metrics across all evaluation criteria. Specifically, DistilBERT outperformed the CNN-LSTM-based models (3-LSTM, CNN-LSTM, 2CNN-LSTM, and 3CNN-LSTM), with an accuracy of 99.65%, precision of 0.992188, recall of 1, F1-score of 0.996078, and ROC-AUC of 0.996894. In contrast, the 3CNN-LSTM model showed the weakest performance with an accuracy of 91.71%, followed by 2CNN-LSTM at 96.96%. Such good performance from DistilBERT has been attributed to the transformer-based architecture of this model. Indeed, it is very good at catching long-range dependencies and subtle contextual information. On the contrary, CNN-LSTM-based architectures sequentially process information and use static embeddings such as GloVe; hence, failing to adapt to the complications that may be present within a dataset.

The results demonstrated that the DistilBERT model outperformed all CNN-LSTM variants across all metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. Importantly, while CNN-LSTM models relied on GloVe-300 embeddings, the DistilBERT model leveraged its pre-trained transformer embeddings, highlighting its ability to dynamically adapt to contextual nuances in the data. This distinction emphasizes the superiority of DistilBERT's dynamic embeddings over static embeddings like GloVe-300 for the task of fake news classification.

The results of this study align with prior research indicating the superiority of transformer-based models for text classification tasks. State-of-the-art models such as BERT and RoBERTa have demonstrated high accuracy in text classification tasks by leveraging contextualized word embeddings and self-attention mechanisms. DistilBERT, a distilled version of BERT, inherits these advantages while reducing computational overhead, making it particularly suitable for real-world applications.

For example:

1. Wani et al. (2021) reported approximately 95% accuracy using BERT for COVID-19 fake news classification.
2. Karande et al. (2021) achieved 95.32% accuracy using a BERT-based approach for social media stance detection.

The proposed DistilBERT model outperformed these results, achieving a higher accuracy and recall. This improvement can be attributed to the extensive preprocessing techniques employed in this study, which reduced noise in the dataset, and the inherent efficiency of DistilBERT in capturing long-range dependencies and subtle contextual nuances.

The application possibilities of DistilBERT lie in incorporating the same into an automated fake news detection system that can be deployed on social networking sites such as Facebook. It should be able to yield exact results across all types of heterogeneous data in bulk. However, computational cost, although reduced from BERT, can again become a problem for very resource-constrained applications or applications that need to be performed in real-time. Probable lightweight transformer models or hybrid architectures are potential future research directions that try to strike a proper balance between accuracy and efficiency.

Although the dataset used from Kaggle is somewhat balanced, every possibility of biases arising because of data imbalance can be accounted for. Different preprocessing techniques, such as uniform sampling and word embedding for vectorization, have been performed in the presented work to nullify these effects. However, residual biases may remain because they are inherently designed to represent variation in different styles of writing of fake and true news. Advanced techniques, such as data augmentation or adversarial training, can be used in future works to make the model more robust against these biases.

The performance of DistilBERT is relatively better than just CNN-LSTM but shows competitive results compared to larger transformer-based models like BERT or RoBERTa; however, DistilBERT reaches comparable accuracy while keeping computational efficiency, hence being attractive for practical applications. However, the dependency on quality labeled data and heavy computational resources points at least to two fields that deserve further optimization and innovation for them to be more accessible and applicable under diverse real-world conditions.

While DistilBERT is computationally lighter than BERT, still resource-consuming, particularly for systems with resource limitations in real-time applications. This reliance upon pre-trained embeddings, both from GloVe and DistilBERT, restricts adaptability to domain-specific nuances not represented within the pre-training corpus. Similarly, static embeddings, such as those provided by GloVe in CNN-LSTM models, don't capture variability and are, therefore, less effective than transformer-based architectures. Second, this work has not compared DistilBERT against other state-of-the-art transformers such as RoBERTa and XLNet. Finally, other interesting avenues for future research include the following: the combination of DistilBERT with other recent variants of transformers, advanced preprocessing by data augmentation or adversarial training, and the development of hybrid architectures that leverage the best from CNN-LSTM and transformers. Overcoming these limitations might result in even more robust, efficient, and generalizable models for fake news detection in practical scenarios.

A separate discussion can also be made about the confusion matrix. The confusion matrix for the DistilBERT model demonstrates outstanding classification performance in distinguishing fake and real news. As shown in Figure 7, the model correctly classified 98% of fake news as fake, with a minor 1.8% false positive rate, where some fake news was misclassified as real. Notably, the model achieved perfect recall (100%) for real news, meaning it did not misclassify any real news as fake. The high precision (98.18%) and recall (98%) for fake news, along with a near-perfect F1-score (98.09%), confirm the model’s robustness. These results indicate that DistilBERT effectively captures contextual patterns in text, minimizing errors, though a slight tendency remains to misclassify a small fraction of fake news as real.

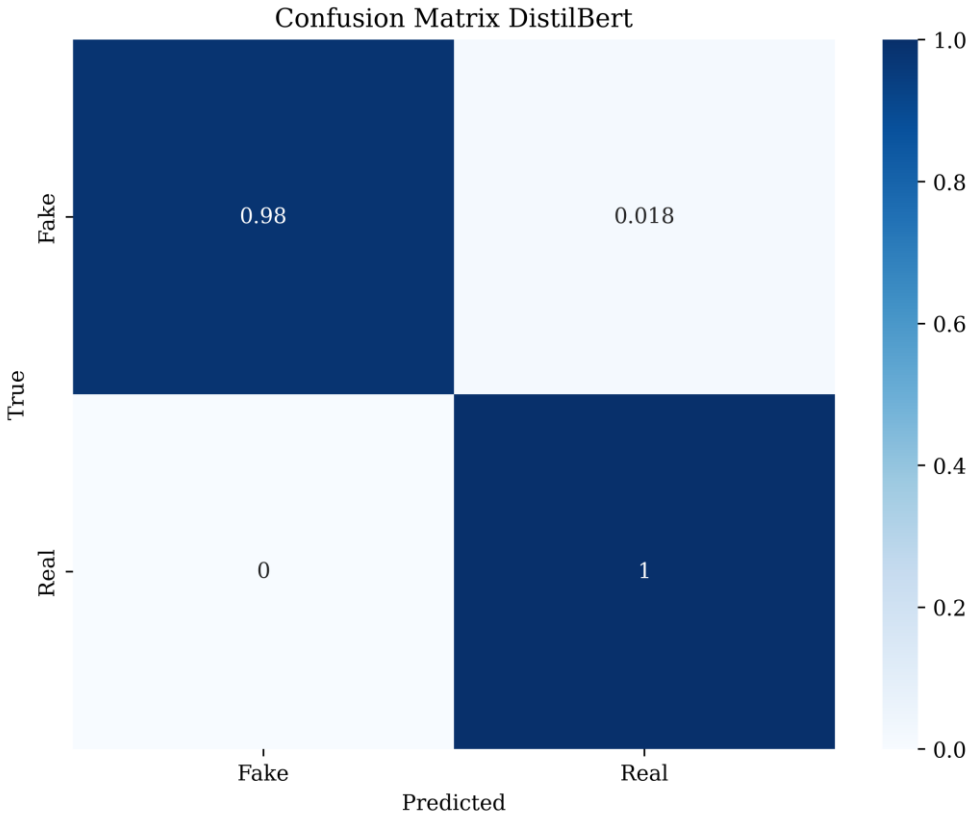


Figure7: Confusion matrix for the DistilBERT model.

Computational feasibility is crucial for real-world applications because the amount of time required for model training and inference time are of dual importance in practical applications. These values are examined in Table 3.

Table 3: Training and inference times for all models.

Model	Accuracy	Training_ Time_relative	Inference_ Time_relative
3-LSTM	0.9802	1.429	1
3CNN-LSTM	0.9171	1.786	1.312
2CNN-LSTM	0.9696	1.571	1.188
CNN-LSTM	0.9793	1	1.062
DistilBERT	0.9965	4.286	3.312

Figure 8 how well DistilBERT classifies fake and real news, the ROC curve indicates almost perfect classification performance: AUC equal to 0.999709 against fake news and 0.999711 against real news. Indicating that the model scored extremely high true positive rates while keeping very low false positive rates, which proves its extreme reliability for misinformation detection. The curve is practically at the top-left corner, meaning it falsely classifies very few instances of fake news as real and vice versa. Such performance indicates that DistilBERT is a robust tool for fake news detection. Nevertheless, despite the very high AUC values, further working on false positives and false negatives is critical due to the potential societal consequences of these classification errors. A single false positive could amplify a significant misinformation story, while an equal number of false negatives could discredit a legitimate story, so it is important to scrutinize patterns of errors and model bias for deployment in the real world.

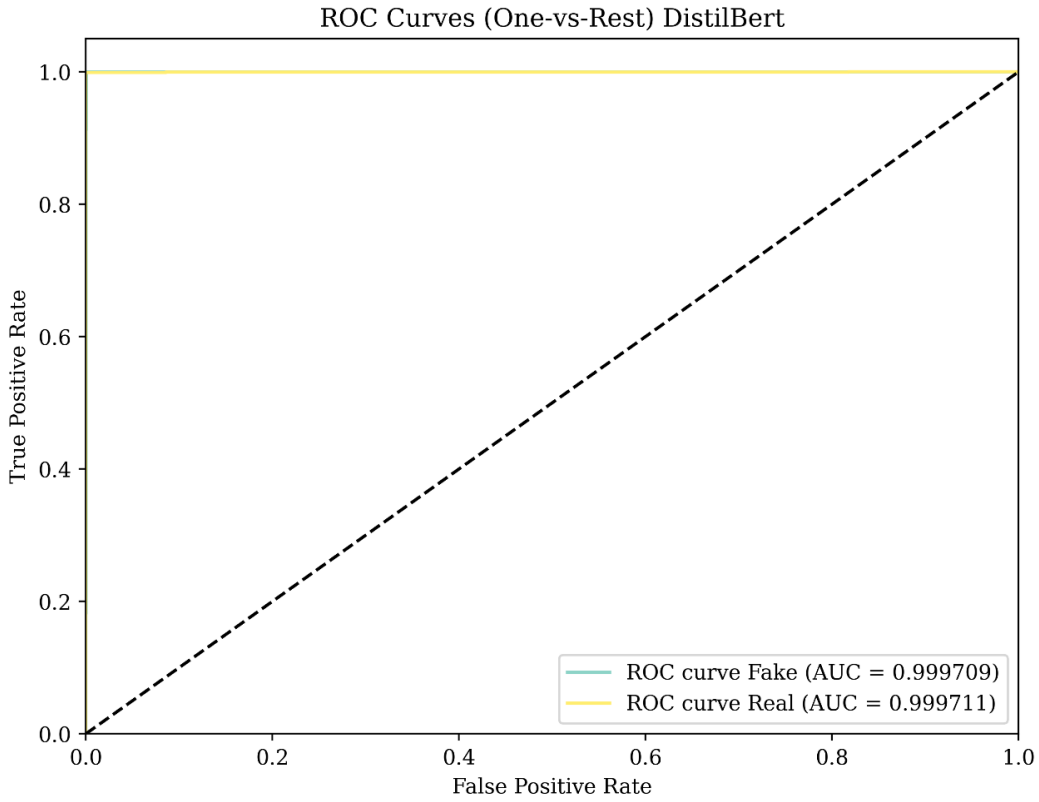


Figure 8: Classifies fake and real news by DistilBERT model.

4 Conclusions

The categorization of Fake and True news was assessed in this study. Because time categorization and accuracy in important occurrences are required. As a result, having trustworthy categorization algorithms is critical. As a consequence, evaluate 5 DL approaches often employed in this industry to select the one that finally performs the best. 5 classification approaches include the Distilbert, 3-layer-long short-term memory, one, 2, and 3-layer-convolutional neural network-long short-term memory. In addition, multiple techniques were evaluated using the performance measures accuracy, precision, recall, F1-score, and ROC-AUC. The following are the important findings of this study:

The Distilbert model has greater accuracy, precision, recall, F1-score, and ROC-AUC metrics than other models. Furthermore, the Distilbert model has a recall value of one.

3-Layer-long short-term memory outperforms convolutional neural network-long short-term memory models.

Although the performance of the 3-layer CNN-LSTM model was reasonable, the efficiency and accuracy of DistilBERT were far more superior to it. Increasing the depth of architecture can improve feature extraction, but going beyond a few layers results in diminished returns, extra computational complexity, and potential for overfitting. The trend in performance suggested that although the 3-layer CNN-LSTM model was competitive, a 2-layer model had a better bargain on accuracy versus efficiency. Hence, yes, deeper CNN-LSTM architectures can improve classification to some extent. The best trade-off between complexity and performance, however, lay with the shallower models, as DistilBERT outperforms all CNN-LSTM variants.

The classification model became weaker as the number of layers in convolutional neural network-long short-term memory models increased. As a result, the 3-layer convolutional neural network-long short-term memory model performs worse than the 2-layer and one-layer convolutional neural network-long short-term memory models.

Nomenclature

Nomenclature		Greek letters	
Abbreviations		Latin Symbols	
NLP	Natural Language Processing	σ	Logistic Function
FN	False News	h_{t-1}	Memory Cell Target
CIA	Computational Intelligence Approaches	x_t	Input Vector
CNN	Convolutional Neural Network	h_{t-1}	Previous Hidden Cell State

LSTM	Long-Short-Term Memory Network	W_{ih}, W_{ix}	Weight Matrix of the Input Gate
BERT	Bidirectional Encoder Representations from Transformers	b_i	Bias of the Input Gate
LR	Logistic Regression	W_{fh}, W_{fx}	Input and Recurrent Weight Matrices
SVC	Linear Support Vector Classification	I_t	Input Gate
DT	Decision Tree	F_t	Forget Gate
RF	Random Forest	O_t	Memory Cell Output
GA	Genetic Algorithm	C_t	Memory Cells
KNN	K-Nearest Neighbor	S_t	Hidden State
		TP	True Positive
BEL	Bagged Ensembled Learning	FN	False Negative
UCRED	User Credibility	TN	True Negative
RELU	Rectified linear unit	FP	False Positive
		Acc	Accuracy
		Pre	Precision
		$f1$	F1-score

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Competing of interests

The authors declare no competing of interests.

Authorship contribution statement

YC performed Data collection, simulation and analysis. BY evaluate the first draft of the manuscript, editing and writing.

Data availability

Data can be shared upon request.

Declarations

Not applicable

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.

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Ethical approval

The research paper has received ethical approval from the institutional review board, ensuring the protection of participants' rights and compliance with the relevant ethical guidelines.

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Breast Mass Segmentation via Enhanced U-Net++ Using Gradient and Contrast Information Reconstruction

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This study introduces an innovative image enhancement technique to enhance breast mass segmentation in mammograms, where edge gradients are frequently feeble and concealed by adjacent tissues. The method combines gradient and contrast information reconstruction to improve essential structural aspects. Gradient reconstruction utilizes a total variation-based model integrated with Haar wavelet transform (HWT), efficiently attenuating high-frequency noise while retaining low-frequency structural details crucial for accurate mass boundaries. Edge features are obtained via the Scharr operator and enhanced through K-Singular Value Decomposition (K-SVD) dictionary learning, which develops adaptive basis functions to denoise and sharpen mass edges. Structural and edge reconstructions are linearly combined with weights of 0.7 and 0.3, respectively, resulting in improved images. The enhanced images are segmented utilizing a U-Net++ architecture, trained with a learning rate of 0.001, a batch size of 4, and the Adam optimizer, incorporating fivefold cross-validation for a thorough assessment. Experiments were performed on 60 mammographic images from the DDSM-BCRP subset, expanded to 360 samples. The proposed method attained a Dice coefficient of 96.52%, an IoU of 93.30%, a sensitivity of 96.56%, and an accuracy of 98.84%, surpassing baseline models. The enhanced segmentation enables more precise lesion localization within Computer-Aided Diagnosis (CAD) systems, thereby aiding in the early detection of breast cancer. Currently, validation is constrained to a modest dataset; subsequent efforts will aim to broaden the methodology to encompass larger, multi-institutional datasets to improve generalization.

Povzetek: Opisan je izboljšan algoritem U-Net++ z rekonstrukcijo gradienta in kontrasta za natančnejšo segmentacijo prsnih mas na mamogramih, s čimer bistveno izboljša natančnost CAD sistemov.

1 Introduction

Breast cancer continues to be one of the most fatal diseases affecting women globally, with mammography utilizing molybdenum target imaging as a primary screening method. Accurate mass segmentation is hindered by acquisition errors, tissue overlap, and scattering noise that conceal lesion boundaries. Diagnostic variability resulting from disparities in radiologists' expertise and human visual perception, including challenges in identifying small contrasts, exacerbates segmentation difficulties. Contemporary techniques frequently necessitate manual involvement and are only partially automated, constraining real-time application. Consequently, the integration of advanced segmentation approaches with Computer-Aided Diagnosis (CAD) systems has emerged as a pivotal objective to enhance the efficiency and reliability of mass detection for early breast cancer diagnosis.

In the present up-to-date practice, two primary medical image segmentation (MIS) methodologies are widely used: traditional ones and deep learning (DL) approaches. Traditional groups mainly include typical edge detection [1–3], region growing [4], and fuzzy clustering algorithms [5–7]. These methods generally have simple operations and perform well on simple images, but they often only consider a single grayscale factor. For molybdenum target images with uneven grayscale distribution, the segmentation performance of traditional methods is unsatisfactory. Recently, the U-Net++ network [8] has demonstrated remarkable segmentation performance in medical imaging, including brain tumors and pulmonary nodules, by improving feature fusion via restructured skip connections and dense blocks. This framework facilitates the adaptive incorporation of intricate features and overarching context, enhancing boundary precision. This work employs U-Net++ for breast mass segmentation in molybdenum target mammograms, using these characteristics. In mammographic pictures, the border gradients of breast masses frequently demonstrate weakness and exhibit low contrast compared to adjacent glandular and adipose tissues. The amalgamation of intensity profiles renders the mass edges visually

indistinguishable from neighboring areas, complicating precise border detection and segmentation for traditional techniques. Utilizing low-quality images characterized by inadequate clarity and contrast for training may hinder the network's ability to discern precise boundaries, leading to incomplete segmentation and diminished accuracy.

Efficient image enhancement and network selection are crucial for optimizing breast mass segmentation in molybdenum target mammograms by more effectively delineating lesion boundaries, forms, and textures. This article presents an enhancement approach that integrates gradient reconstruction with contrast enhancement, subsequently employing a U-Net++ network for segmentation. Comparative tests were performed utilizing four datasets: original images, gradient-enhanced images, contrast-enhanced images, and photos altered with recognized enhancement techniques. Performance was assessed with the Dice coefficient, Intersection over Union (IoU), sensitivity, and accuracy. Additionally, relative studies use the suggested enhancement approach and the U-Net and U-Net++ networks. Visual analysis and impartial assessment of the SRs demonstrate that the technique suggested in this work, when applied to the U-Net++ network, exhibits superior segmentation performance compared to the unprocessed dataset and outperforms current advanced segmentation networks.

Progress in artificial intelligence (AI) has markedly enhanced pattern recognition tasks such as semantic segmentation [9,10], facilitating accurate item delineation in intricate images. Deep learning (DL) models are particularly adept at breast mass segmentation due to their automatic feature learning and structural representation, which improve boundary and texture detection.

1.1 Literature review

Oliveira et al. [11] assessed U-Net and U-Net++ for segmenting breast tumors in ultrasound images utilizing the BUSI dataset. Both models were trained for 1000 epochs utilizing data augmentation and an IoU-based loss function. U-Net++ surpassed U-Net, with a Dice score of 75.71% on validation data, 88.60% on test data, and an F1-score of 94% in tumor classification. The authors proposed enhancing performance by utilizing larger datasets and optimizing hyperparameters. Wisaeng [12] presented U-Net++DSM, a brain tumor segmentation technique that integrates U-Net++ with deep supervision and a dilation operator, demonstrating robust performance on constrained MRI data. Evaluated using public datasets, it surpassed conventional U-Net and other methodologies, achieving a 98.02% Dice score, 98.64% accuracy, and above 98% sensitivity and specificity, so illustrating its efficacy in pixel-level categorization. Tiryaki [13] proposed a cascaded deep transfer learning methodology for the segmentation and classification of breast masses utilizing mammograms. The U-Net++ model with an Xception encoder attained a Dice score of 0.6356, an IoU of 0.5408, and an AUC of 0.7829 for segmentation, along with an AUC of 0.8188 and an accuracy of 76.19% for classification, demonstrating its potential to aid diagnosis in the absence of clinical data. Ronneberger et al. [14] introduced U-Net, characterized by a symmetric "U"-shaped encoder-decoder architecture that integrates low-level spatial and high-level semantic data via skip links. Despite being a traditional model for medical image segmentation (MIS), U-Net's inflexible feature fusion frequently results in redundant learning and elevated training expenses. Zhou et al. [8] introduced the U-Net++ architecture, an enhancement of U-Net that incorporates several stacked U-Nets at varying depths. U-Net++ reconfigures skip connections by incorporating intermediary dense convolutional layers between the encoder and decoder, facilitating more adaptable and gradual feature fusion. It employs model pruning during training to eliminate redundant neural pathways, thereby decreasing network complexity and enhancing inference speed without compromising segmentation accuracy. Zhou et al. [15] proposed ATFE-Net to improve long-range dependency capture and feature integration for breast mass segmentation. By enhancing global context understanding, ATFE-Net outperformed conventional local feature-based methods, achieving Dice coefficients of 82.46% on the BUSI dataset and 86.78% on the UDIAT dataset for large-scale mass segmentation. Malekmohammadi et al. [16] proposed a fully automatic 3-D ABUS breast mass segmentation by combining a tumor detection network with a Bidirectional Convolutional Long Short-Term Memory (Bi-ConvLSTM) and a segmentation network with a 2-D attentive UNet. The saliency maps and enhanced attention modules increased the precision, while the Convolutional Block Attention Module handled variations of mass size. It reached a Dice similarity index of 85.82% for 60 ABUS volumes. Yaqub et al. [17] have suggested a DL concept for the diagnosis of breast cancer utilizing mammogram images, where segmentation is by Attention-Constrained Adaptive Atrous U-Net (ACA-ATRUNet), and classification is done by Attention-Constrained Adaptive-Multidimensional Network (ACA-AMDN). The proposed framework has segmented and classified the breast masses effectively while optimized by the Multi-Model Learning Optimization for Enhanced Output Optimization (MML-EOO) algorithm, showing superior performance that could enhance mammogram-based cancer screening. Rahman et al. [18] established a ResNet-50 framework utilizing transfer learning to classify INbreast mammograms as benign or malignant, achieving 93% precision. Deep learning (DL) enhances diagnostic precision by autonomously extracting nuanced image characteristics, facilitating early breast cancer identification and augmenting the dependability of computer-aided detection (CAD) systems. Mahmood et al. [19] created a Convolutional Neural Network (CNN) that attained 0.97 test accuracy, 0.99 sensitivity, 0.98 training accuracy, and 0.99 Area Under the Curve (AUC) for accurately classifying breast masses in mammograms. The model facilitates quicker treatment planning and diagnosis by utilizing improved data augmentation, transfer learning, and preprocessing on private and Mammographic Image Analysis Society (MIAS) datasets. Almalki et al. [20] introduced an image enhancement scheme to mammograms, including a step on low contrast and

background noise suppression by Principal Component Analysis (PCA), morphological processing, and coherence enhancement with LoG and diffusion filters. The method was evaluated on 11,194 images, where an improved peak signal-to-noise ratio, difference, and Enhancement Measure Estimation (EME) were reported compared to previous approaches, thus improving diagnostic accuracy. Avcı and Karakaya [21] studied the effect of different preprocessing algorithms on the mammography image quality for CAD systems. They proposed a methodology based on the mini-MIAS database: a mixture of median filtering, Contrast Limited Adaptive Histogram Equalization (CLAHE), and unsharp masking (USM) for increasing resolution and visibility; suspicious region extraction by k-means; and classification of lesions by different machine learning approaches. The combination of MF with USM and CLAHE enhanced the accuracy, while the best performances were obtained by Support Vector Machine (SVM), RF, and NNs. This study proved that proper preprocessing is important to differentiate between benign and malignant lesions. Aliniya et al. [22] proposed a hybrid loss function to segment breast cancer, designed to handle pixel class imbalance and mass diversity difficulties. Their method outperformed various up-to-date techniques on a curated breast imaging subset of DDSM and INbreast. This had been in response to the incorporation of mass size and density within both sample-level and region-level loss calculations. Tiryaki [23] introduced cascaded deep transfer learning techniques for mammographic mass segmentation and classification based on the Breast Cancer Digital Repository dataset. The best-performing model was the Unet++ model with an Xception encoder, providing an AUC of 0.7829, a Dice coefficient of 0.6356, and an IoU of 0.5408 for segmentation tasks. Conversely, classification resulted in an AUC of 0.8188 and a precision rate of 76.19% from this model. Hence, the method showed its good promise in the automation of diagnosing breast cancer and alleviating the workload of radiologists.

Wisaeng [24] designed U-Net++DSM, which adds a Deep Supervision Mechanism and a dilation operator to U-Net++. This work used these modifications for brain tumor segmentation. That model provides the following performances: 98.59% sensitivity, 98.64% specificity, 98.64% accuracy, and a 98.02% Dice score. Das et al. [25] suggested a weighted U-Net++ model (WU-Net++) as a DL framework for segmenting brain tumors. This network has been tested on the BraTS 2018 dataset and yielded a Dice score of 0.91 and an AUC of 0.915. It also performed very well in intracranial hemorrhage classification with an accuracy of 0.9949 and multi-organ segmentation, showing its potential in precision medicine. Tambe-Jagtap and Jaaz [26] revealed that genetic and proteomic profiling can improve breast cancer treatment through the facilitation of tailored therapies. Focusing on abnormalities such as TP53 and BRCA1/2 resulted in a 60% reduction in tumors and diminished adverse effects relative to conventional therapies, underscoring the significance of personalized strategies. Houby [27] examined how trends such as transfer learning, active learning, and federated learning augment deep learning in medical imaging by mitigating data constraints, enhancing efficiency, and safeguarding privacy. These methodologies have demonstrated significant potential in recent publications in leading ScienceDirect journals. Shangguan et al. [28] presented ICU-Net, a denoising model for low-dose CT images that employs enhanced ConvNext blocks and attention mechanisms. Utilizing a blended loss to avert over-smoothing, ICU-Net attained enhanced PSNR, SSIM, and RMSE metrics, surpassing current methodologies while maintaining texture fidelity. Chegireddy and Srinagesh [29] created a deep learning framework for the early identification of pancreatic cancer with CPTAC-PDA data. The approach integrated U-Net++ segmentation, HHO-based CNN, and BOVW for feature extraction and selection, alongside VGG16 for classification, attaining an accuracy of 0.96 and surpassing other models.

Notwithstanding the progress of state-of-the-art segmentation networks such as Mask R-CNN, DeepLab, and ACA-ATRUNet, certain restrictions endure. Numerous models encounter difficulties in maintaining border integrity in low-contrast mammograms and demonstrate susceptibility to noise, particularly in thick breast tissues. Moreover, conventional networks are frequently trained on unprocessed pictures, which constrains their efficacy in the presence of gradient transitions or ambiguous lesion boundaries. Our approach directly tackles these challenges by augmenting contrast and structural clarity before segmentation, leading to substantial enhancements in Dice and IoU measures. In response to the reviewer's comments, we meticulously examined the listed references and eliminated those irrelevant to breast mass segmentation or image enhancement in mammographic imaging, so ensuring that all references now closely align with the study's objectives.

Table 1: Comparison of State-of-the-Art Breast Mass Segmentation Methods

Model	Dataset	Dice (%)	IoU (%)	Sensitivity (%)	Accuracy (%)	Reference
U-Net	BUSI	75.17	–	–	–	Oliveira et al. [11]
U-Net++	BUSI	88.60	–	–	90.00	Oliveira et al. [11]
U-Net++DSM	Brain MRI	98.02	–	98.59	98.64	Wisaeng [12][24]
U-Net++ + Xception	BCDR	63.56	54.08	–	76.19	Tiryaki [13][23]
ATFE-Net	BUSI / UDIAT	82.46	–	–	–	Zhou et al. [15]
DeepLabV3+	Private	90.20	82.70	91.50	95.10	Das et al. [25]

ACA-ATRUNet (segmentation)	Mammogram	–	–	–	–	Yaqub et al. [17]
Proposed Method (this work	DDSM	96.52	93.30	96.56	98.84	–

1.2 Research gaps and novelties

This research tackles significant obstacles in breast mass segmentation through mammography by surmounting the shortcomings of conventional and deep-learning methodologies. Traditional techniques, such as edge identification and fuzzy grouping, exhibit suboptimal performance due to the dispersion of grayscale values and indistinct edges resulting from tissue overlap, insufficient lesion contrast, and image noise. Despite advancements in segmentation through deep learning models such as U-Net++, challenges persist with gradual gradient transitions at lesion boundaries and interference from heterogeneous adjacent tissues, especially under conditions of low image quality.

Numerous research persists in the use of unprocessed mammograms, wherein inadequate clarity further diminishes segmentation precision. Recent research underscores the imperative for sophisticated preprocessing methods to improve input quality and maximize the efficacy of deep learning models. This paper proposes an image enhancement technique utilizing Haar wavelet transform (HWT) and K-Singular Value Decomposition (K-SVD) to mitigate noise, sharpen edges, and enhance contrast. Enhanced pictures are segmented with a U-Net++ network with fivefold cross-validation, resulting in a Dice coefficient of 96.52% and an IoU of 93.30%. Comparative trials with alternative enhancement approaches validate the efficacy of the suggested technique in enhancing breast cancer diagnosis and broader medical imaging applications.

To direct this inquiry, we establish the subsequent research questions:

How can gradient and contrast information be utilized to enhance mammographic image quality for deep learning segmentation?

Does the incorporation of augmented picture inputs into U-Net++ enhance segmentation performance compared to standard inputs or single-mode enhancement?

What is the ideal fusion approach for structural and edge-based image components to enhance segmentation accuracy?

1.3 Paper organization

The document is defined in the way as follows: Section 2 explains the aspects of the proposed enhanced image algorithm focusing on gradient and contrast information, reconstruction for better clarity and boundary definition in mammograms, and integration into the U-Net++ network within the framework of five-fold cross-validation. Section 3 provides a detailed explanation of the empirical setup and findings: a dataset and the pre-processing step to show the proposed methodology vis-a-vis all the methods applied herein. In addition, a deeper scrutiny of its effectiveness in light of metrics such as segmentation accuracy, sensitivity, robustness, and generalizability are carried out by comparing the different network performances. Section 4 summarizes the results obtained from this investigation, which are related to the segmentation of breast masses through the proposed methodology, further discussing possible directions for future research on medical images by processing and segmentation.

2 The method for mammographic mass segmentation by fusing gradient and contrast information reconstruction

Segmentation of breast masses presents difficulties owing to the gradual intensity changes at mass boundaries and the poor contrast between lesions and adjacent tissues, which obscure edge delineation and hinder the precise localization of mass margins by both classical and deep learning models. This study presents a segmentation method utilizing the U-Net++ network, augmented by a gradient and contrast information reconstruction process to improve image quality before segmentation. As illustrated in Fig. 1, the method initially reconstructs the gradient information of the mammography to emphasize structural boundaries, thereafter using contrast enhancement to augment the differentiation between masses and surrounding tissues. The amalgamated gradient and contrast data are integrated to produce an upgraded image featuring more defined mass edges and superior lesion-background differentiation. The improved image is subsequently utilized as input for the U-Net++ network, which is trained inside a fivefold cross-validation framework to effectively segment breast masses. Every stage in the flowchart signifies a crucial improvement or segmentation phase aimed at resolving particular imaging challenges. The suggested image enhancement framework amalgamates gradient and contrast data to enhance mammographic mass segmentation. A total variation model is employed for gradient reconstruction to recover structural components and attenuate high-frequency noise while maintaining the integrity of the underlying tissue architecture. Edge enhancement is accomplished through the application of the Scharr operator for fine boundary detection, succeeded by K-SVD dictionary learning for the reconstruction and denoising of edge details. The structural image is deconstructed by the Haar Wavelet Transform (HWT) to distinguish low- and high-frequency subbands for contrast reconstruction. A gamma correction function is utilized on the deconstructed components to adaptively boost contrast, and the altered subbands are recombined to produce the contrast-enhanced image. The gradient- and

contrast-enhanced outputs are linearly combined using empirically established weights (0.7 for structure and 0.3 for edge) to provide the final input image for U-Net++ segmentation. These measures guarantee the preservation and optimization of both edge precision and tissue contrast for subsequent deep-learning efficacy.

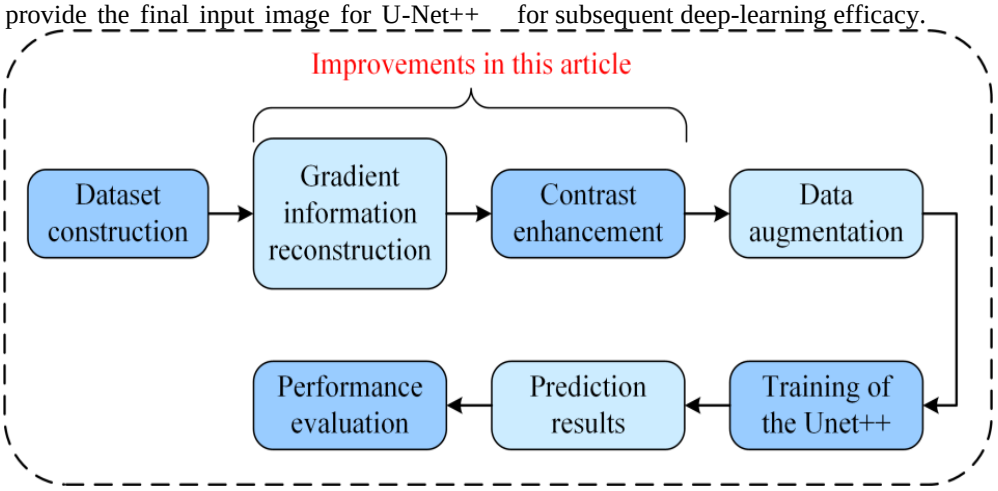


Figure 1: Experimental flow chart

2.1 The Method for Enhancing Masses by Fusing Gradient and Contrast Information Reconstruction

2.1.1 Reconstruction of gradient information

A total variation-based model was utilized to extract the structural components of mammographic pictures due to its adaptability in differentiating structural and textural information without dependence on predetermined texture assumptions. This model employs terms such as $H_x(p)$, $K_x(p)$, and the Gaussian weighting function gp,q to delineate local spatial fluctuations and facilitate precise structure extraction. The regularization parameter λ governs smoothness, with values ranging from 0.01 to 0.03 selected to equilibrate noise reduction and feature preservation. A universal window-based total variation metric H facilitates adaptation across diverse tissue patterns. In Haar wavelet transform (HWT) processing, the low-frequency (LF) subband of the original image is utilized to substitute that of the structure image, thereby reducing information loss caused by pixel averaging. The Scharr operator is favored over the Sobel operator for edge detection due to its superior gradient sensitivity and enhanced border localization. K-SVD dictionary learning improves edge reconstruction by considering each column in the sample matrix Y as a vectorized image patch for sparse representation and denoising. Ultimately, structural and edge pictures are combined using linear weighting (0.7 for structure, 0.3 for edges) derived from experimental optimization, resulting in an enhanced image with more distinct lesion characteristics, as illustrated in Fig. 1.

(1) Extraction of image structural components based on the total variation from the model [30]. In structural component extraction, a model based on the total variation form is used, which can reasonably analyze the structure and texture information of the image without specifying particular texture rules. The model can be represented as:

$$\arg\min_{S} \sum_{p} \left(S_p - I_p\right)^2 + \lambda \cdot \left(\frac{H_x(p)}{K_x(p)+\varepsilon} + \frac{H_y(p)}{K_y(p)+\varepsilon}\right) \tag{1}$$

$$H_x(p) = \sum_{q \in R(p)} g_{p,q} \cdot \left|(\partial_x S)_q\right| \tag{2}$$

$$H_y(p) = \sum_{q \in R(p)} g_{p,q} \cdot \left|\left(\partial_y S\right)_q\right| \tag{3}$$

$$K_x(p) = \left|\sum_{q \in R(p)} g_{p,q} \cdot (\partial_x S)_q\right| \tag{4}$$

$$K_y(p) = \left|\sum_{q \in R(p)} g_{p,q} \cdot \left(\partial_y S\right)_q\right| \tag{5}$$

Where (I) signifies the input image, (p) denotes the index value of 2D image pixels, (O) signifies the output structural image, (q) denotes the pixel index within a square range centered at (p), fixed at 0.001 to prevent division by zero, (λ) is the weight used to adjust the smoothness of the image, generally set between 0.01 and 0.03, the empirical value of the spatial scale parameter is between 0 and 8, which limits the size of the window in formulas (1) to (5), playing a crucial role in the structural extraction process, and (K) represents the Gaussian kernel function, which can be expressed as:

$$g_{p,q} \propto exp\left(-\frac{\left(x_p - x_q\right)^2 + \left(y_p - y_q\right)^2}{2\sigma^2}\right) \tag{6}$$

Due to the diverse texture types in different images, the algorithm does not assume or artificially determine the texture type beforehand. Instead, it adopts a universal pixelized window total variation measure H, where $H_x(p)$and $H_y(p)$ respectively represent the windowed total changes in the x and y directions of the pixels utilized to calculate the absolute spatial differences within the window. $K_x(p)$ and $K_y(p)$ is a new windowed inherent variation utilized to assist in separating the texture from the main structures. This step extracts the structural part

of the molybdenum target image, removes high-frequency information (HFI), and retains only the original image's low-frequency information (LFI) utilized for the following rebuilding of LFI.

(2) Image structure reconstruction based on the HWT. The rebuilding of the structural part of the breast molybdenum target image is carried out using the HWT. The HWT extracts the breast structure image's LF subband and three HF subbands. Since the structural image has already lost some information compared to the original image, and when extracting the LF subband using the HWT, a "mean" method is applied to compress the number of pixels, resulting in a lower-resolution image. This means that this subband has lost some information, so the LF subband of the structural image is discarded. The LF subband obtained by performing the HWT on the original image is used to replace the LF subband of the structural image, and wavelet reconstruction is conducted with the three HF subbands of the structural image. The LF subband of the original image contains rich LFI, while the three HF subbands contain the singular characteristics of the LFI. This avoids the problem of dimension mismatch between subbands during wavelet reconstruction and maximizes the preservation of the LFI of the image.

(3) Extraction of image edge parts based on gradient operators. The edge part of the image is the most critical HFI in the molybdenum target image, and this HFI is vital in the subsequent segmentation of tumor edges. An edge is the endpoint of one region and the starting point of another area, so the grayscale information at the edge has abrupt changes. Objects and backgrounds can be segmented based on this characteristic. This study mainly uses the Scharr operator to extract the edge information of tumors. Compared to the commonly used Sobel operator, the Scharr operator, with the same computational complexity and speed, has different convolution kernel coefficients. The Scharr operator is more sensitive in extracting edge localization information than the Sobel operator and can capture finer boundary information. It succeeds in isolating the HFI from the image. In that sense, the process provides the grounds for further gradient reconstruction of edge images.

(4) Image edge reconstruction based on K-SVD learning. The method utilizes K-SVD dictionary learning to train the dictionary for extracting the edge part of the breast image. This step is known as "sparse coding" to learn the dictionary D during the training phase. From the basic matrix analysis theory, sample Y should be viewed as a matrix, where each column represents a set of samples. The Y matrix is decomposed into D and X matrices through dictionary learning. This process can be represented by formula (7).

$$Y \approx D * X \tag{7}$$

Where D represents the dictionary structure, each column of D is called an atom, and X represents the encoding vector. Every column of D is a normalized vector, and X should be as sparse as feasible. The objective function of dictionary learning is:

$$D、X = \begin{cases} \underset{D、X}{argmin} \|Y - DX\| \\ \|X\|_0 \le L \end{cases} \tag{8}$$

The parameter L is the sparsity constraint parameter. Since the objective function involves two unknown variables, this algorithm's solution process involves fixing one variable, updating the other variable, and then updating them alternately.

This paper uses sparse coding to denoise breast edge images. Since breast edge images are composed of noise-free and noisy images, sparse operations can be performed on the original noise-free images, expressed in the form of a finite number of "atoms." The noisy images are non-sparse, so the K-SVD dictionary training is utilized to extract the sparse components of the image, which are then reconstructed to attain the denoised image. This procedure reconstructs the HFI of the molybdenum target image, namely the reconstructed image of the breast lump edge.

(5) Linear weighting. In Eqs. (1) and (4), the reconstructed images of the breast structure and edge parts have been obtained. These two parts are linearly weighted. After multiple experiments, the weight of the structural reconstruction image is fixed at 0.7, and the weight of the edge reconstruction image is fixed at 0.3. Finally, the gradient information reconstructed image with more prominent lesion information is obtained. The final improved image is generated by integrating structural and edge reconstructions through a linear weighting technique, employing a ratio of 0.7 for structure and 0.3 for edge. The weighting was empirically determined by assessing segmentation performance (Dice and IoU) across several configurations; the 0.7:0.3 ratio consistently provided the optimal compromise between maintaining anatomical boundaries and reducing noise. K-SVD dictionary learning was utilized for edge enhancement, employing a dictionary including 256 atoms, a patch size of 8×8 pixels, and a sparsity constraint permitting a maximum of 5 non-zero coefficients per patch. The parameters were optimized to accurately capture high-frequency edge structures while minimizing noise. During the contrast reconstruction step, gamma correction was implemented with a gamma value of 4. This value was selected after assessing several gamma values, with $\gamma = 4$ providing optimal visual augmentation of low-intensity areas without oversaturation and enhancing segmentation uniformity in first trials. These configurations were tuned to provide efficient pre-processing before U-Net++ segmentation.

Input: Original mammographic image I
Output: Enhanced image I_enhanced
Step 1: Gradient Reconstruction
2. Extract structural component S from I using total variation (TV) model
3. Replace LF subband of S with that of I using Haar Wavelet Transform (HWT)
4. Apply Scharr operator to I for edge detection → obtain edge map E
5. Apply K-SVD dictionary learning to E → denoised edge map E_denoised
6. Linearly combine S and E_denoised:

```
    I_gradient = 0.7 * S + 0.3 * E_denoised
Step 2: Contrast Enhancement
8. Decompose I_gradient using HWT into LF and HF subbands
9. Apply gamma correction (γ = 4) to LF subband
10. Reconstruct contrast-enhanced image I_contrast using corrected LF and original HF subbands
11. Set I_enhanced ← I_contrast
12. Return I_enhanced
```

2.1.2 Contrast reconstruction

The operation in Section 1.1.1 can effectively reduce the noise around the mass, making the gradient of the mass boundary larger and, to some extent, overcoming the problem caused by the gradual change in the characteristics of breast lesion edges. However, because the difference between the lesion area and the surrounding glandular tissue in the mammographic image is not distinct enough, enhancing the contrast is particularly important. Applying the gamma transformation, it is easy to know that if $\gamma>1$, higher grayscale values of an image are stretched while the lower grayscale values are squeezed. In case $\gamma<1$, the lower grayscale values are stretched, and the higher grayscale values are squeezed. So, in this paper, γ is fixed as 4, which markedly increases the contrast between the mass and the surrounding area, and the mass becomes very clear. The suggested image enhancement architecture to address noise, edge gradients, and inadequate contrast to improve breast mass segmentation in mammograms is shown in Fig. 2. LF features are preserved. In contrast, the structural portion of the image is refined using wavelet reconstruction after being retrieved using a total variation-based model. The Scharr operator collects the edge information to reduce noise and define boundaries, which is then improved via K-SVD dictionary learning. The structural and edge components are linearly weighted (0.7 and 0.3) to create a gradient-enhanced image. The image is then subjected to gamma treatment (γ=4) to improve contrast and highlight the lesion. Breast mass visibility and segmentation accuracy are much increased by this method.

Fig. 2. Flowchart for the improvement of molybdenum target images via gradient and contrast reconstruction techniques. Initially, structural information is obtained by a total variation (TV) model and Haar wavelet transform (HWT). Edge information is augmented with the Scharr operator and subsequently denoised through K-SVD dictionary learning. Gradient and contrast data are recreated independently: gradient enhancement accentuates lesion borders, whilst contrast enhancement is executed by gamma transformation following wavelet decomposition. Structural and edge reconstructions are subsequently integrated via linear weighting to get an improved image with more distinct mass features for U-Net++ segmentation.

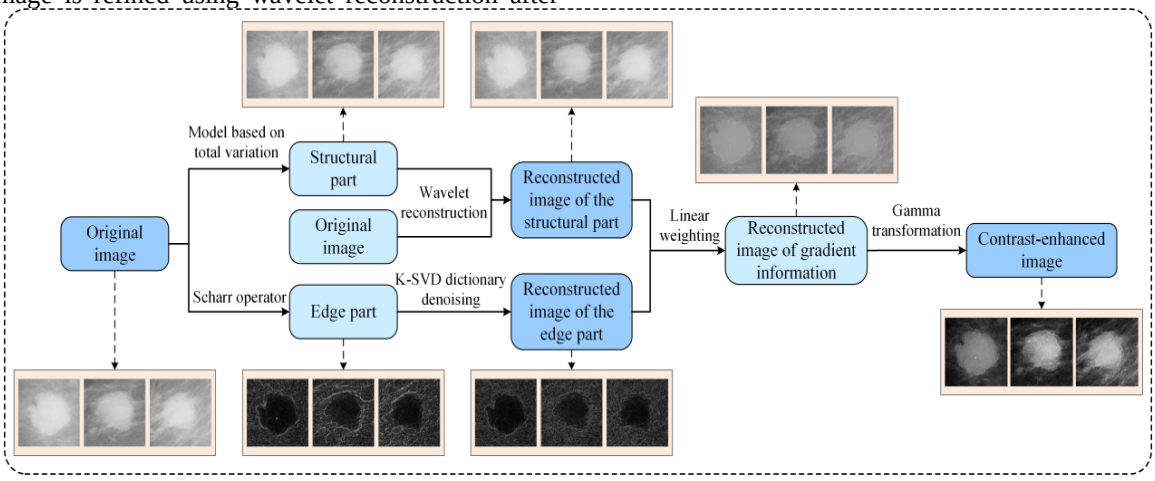


Figure 2: Molybdenum target image enhancement flow chart based on gradient information and contrast reconstruction

2.2 Breast Mass Segmentation Based on U-Net++

After enhancing the images using the method in Section 1.1, this study employs the U-Net++ network for breast mass segmentation. The U-Net++ network is an improvement based on the U-Net network, where features at each level are fully integrated using skip connections. During network training, the network autonomously learns features at different levels. This network adopts a nested structure, equivalent to concatenating four U-Net models of various depths. The U-Net substructures of different depths share a feature extractor, significantly reducing training time. Each U-Net sub-network output is supplemented with deep supervision, adding 11 convolutional kernels to detect the production of each U-Net sub-network. In the U-Net++ segmentation system, every intermediate decoder node is linked to a deep supervision branch to enhance gradient propagation and promote early feature refining. A convolutional layer is performed, followed by a 1×1 convolution operation,

resulting in 11 feature maps. The convolutional kernels are initialized randomly and modified by backpropagation during the training process. The number 11 was empirically chosen to optimize the balance between segmentation detail acquisition and network complexity. Deep supervision across many semantic levels enhances the model's ability to generate more coherent and precise mass segmentations by directing intermediate representations towards the ultimate segmentation goal.

The outputs of each U-Net sub-network are not directly connected to the final output, allowing for model pruning and flexible selection of network depth through pruning operations. During training, the input images undergo forward propagation, and the pruned parts can assist in weight updates for the remaining parts during backpropagation. During testing, only forward propagation is performed on the input images, and the pruned parts have no impact on the output results, significantly reducing the parameter count and improving testing speed. Therefore, this study uses the U-Net++ network for breast mass segmentation.

3 Experimental Results and Analysis

3.1 Experimental Data and Experimental Settings

This experiment's breast molybdenum target image data is from the Breast Cancer Resistance Protein (BCRP) subset of the DDSM. For the 60 samples with prominent masses, the interested regions were cropped to obtain images with a size of 256x256 and a bit depth of 8 bits. Data augmentation was conducted on these 60 samples to avoid overfitting during training. The label images were annotated using LabelMe software, resulting in a total of 360 image samples and label samples. All experiments were performed on a workstation equipped with an NVIDIA RTX 3090 GPU (24 GB VRAM), 128 GB RAM, and an Intel Core i9 processor, operating on Ubuntu 20.04 with Python 3.9, TensorFlow 2.10, and Keras 2.7.

The experiment employed five-fold cross-validation to compare the SRs of datasets with various augmentation operations input into U-Net++. Four loss curves and objective evaluation metrics were provided for four different scenarios. The experiment set the learning rate to 0.001, each batch contained four training samples, the epoch was set to 100, and the model utilized the Adaptive Moment Estimation (ADAM) optimizer to dynamically adjust the update step size. The loss values were recorded during training, the best training model was saved, and this model was used for testing. Sixty mammography pictures featuring breast masses were extracted from the dataset. To prevent overfitting during training, data augmentation was implemented on these samples, incorporating random rotations between –15° and +15°, horizontal and vertical flips, scaling variations of ±10%, and minor brightness modifications. These augmentations augmented sample variety and improved model generalization.

The Adaptive Moment Estimation (Adam) optimizer was employed for model optimization, utilizing an initial learning rate of 0.001, with β_1 configured to 0.9 and β_2 to 0.999. Adam dynamically modifies the learning rate for each network parameter by assessing the first and second moments of gradients, promoting steady and efficient convergence throughout training. The U-Net++ network was trained using a batch size of 4, and fivefold cross-validation was conducted to enhance robustness and reduce bias in performance assessment. The learning rate of 0.001 and batch size of 4 were determined through initial experiments aimed at optimizing validation Dice scores. The Adam optimizer was selected for its demonstrated efficacy in training deep networks with moderate dataset sizes. No substantial improvements were noted with reduced learning rates or increased batch sizes. Five-fold cross-validation was selected to ensure statistical rigor and reduce overfitting, especially due to the limited sample size. This technique offers a dependable assessment of model generalization by guaranteeing that each sample is included in a test fold precisely once. Data augmentation was conducted on all 60 original photos through random rotation (±10 degrees), horizontal flipping, scaling (90–110%), and minor intensity variation. The modifications were uniformly implemented throughout all five folds to ensure consistency in the distribution of training and validation data. The linear fusion weights (0.7 for structural reconstruction and 0.3 for edge reconstruction) were experimentally determined after numerous attempts utilizing weight combinations from 0.1 to 0.9. The chosen ratio consistently produced the optimal segmentation metrics (Dice and IoU) across validation folds.

3.2 Evaluation Metrics

3.2.1 Image enhancement evaluation metrics

To make the enhanced effect of the image more intuitive, this paper uses two evaluation metrics, Spatial Frequency (SF) and Average Gradient (AG), to evaluate the image enhancement effect [31]. SF and AG are represented by Eqs. (9) and (12), respectively.

Spatial Frequency (SF) quantifies the overall detail and textural complexity present in an image. It illustrates the swift alterations in intensity across various sections of the image, including both horizontal and vertical fluctuations. A high SF value signifies that the image exhibits finer structural details and sharper transitions between various regions, leading to visibly cleaner edges and more complex texture patterns. A low SF value indicates that the image is smoother and morefuzzy, exhibiting diminished structural information and fewer well-defined boundaries. This study employs SF to statistically evaluate the efficacy of image enhancement techniques in preserving fine structures and enhancing mass visibility.

$$SF(I) = \sqrt{RF^2 + CF^2} \tag{9}$$

$$RF = \sqrt{\frac{1}{MN}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\left(I(i,j) - I(i,j+1)\right)^2} \tag{10}$$

$$CF = \sqrt{\frac{1}{MN}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\left(I(i,j) - I(i+1,j)\right)^2} \tag{11}$$

$$AG(I) = \frac{1}{(M-1)(N-1)}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\sqrt{\frac{\left(I(i+1,j) - I(i,j)\right)^2 + \left(I(i,j+1) - I(i,j)\right)^2}{2}} \tag{12}$$

Here, I signifies the input image, RF signifies the row frequency, CF denotes the column frequency, and M and N denotes the height and width of the image. The SF of an image can also reflect the grayscale variation rate of the image. In an image, different components correspond to different spatial frequencies. For example, edges represent the highest SF of pixel detail information, while backgrounds represent lower spatial frequencies of large flat areas. Therefore, the higher the SF, the higher the visual clarity of the pixels and the more pronounced the detailed information content of the image. AG can also be an essential criterion for determining image clarity. Generally, the larger the AG, the higher the image clarity.

3.2.2 Image segmentation evaluation metrics

In medical image processing, to objectively and quantitatively analyze and evaluate SRs, people often compare the SRs of algorithms with labels at the same pixel level. The Average Gradient (AG) is a crucial metric for image sharpness, denoting the mean magnitude of intensity variations between neighboring pixels throughout the image. An elevated AG value indicates more abrupt intensity shifts, resulting in borders and boundaries within the image seeming more distinct and visually defined. A diminished AG value signifies more uniform intensity fluctuations, resulting in indistinct or poorly delineated edges. This study utilizes AG to assess the efficacy of enhancement techniques in refining image borders, highlighting distinct mass contours essential for precise segmentation. The metrics used in this article include IoU, Precision, Sensitivity, F1-Score (Dice Coefficient), Specificity, and Accuracy, defined as [32] :

$$IoU = \frac{TP}{FN + FP + TP} \tag{13}$$

$$Precision = \frac{TP}{TP + FP} \tag{14}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{15}$$

$$F1 - Score = \frac{2TP}{2TP + FP + FN} \tag{16}$$

$$Specificity = \frac{TN}{TN + FP} \tag{17}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

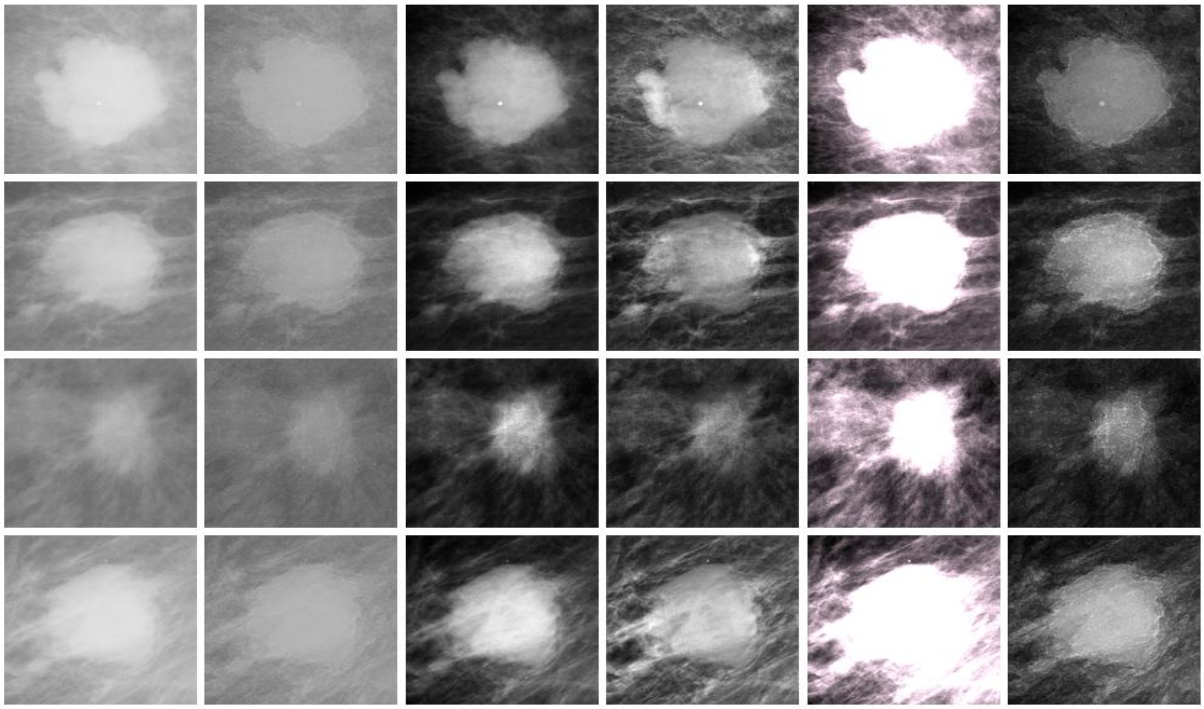
Among them, TP (True Positive) represents true positives, where "True" indicates correct predictions, meaning the prediction is consistent with the actual situation, and "Positive" refers to positive or positive samples. FN (False Negative) signifies false negatives, where "False" indicates incorrect predictions, meaning the prediction is inconsistent with the actual situation, and "Negative" refers to negative or negative samples. Similarly, TN (True Negative) denotes true negatives, and FP (False Positive) signifies false positives.

IoU is the ratio between the intersection and union of the SR and the label. Precision, also known as Positive Predictive Value or Class Pixel Accuracy. Sensitivity, also referred to as Recall or TP Rate, represents the ratio of the SR to the label, reflecting the ability to identify pixels in the ROI. Meanwhile, the Dice coefficient represents the ratio of the intersection of two objects to the entire area in image segmentation problems. The mathematical formula for the Dice coefficient is the same as that for F1-Score, described as the harmonic mean between Precision and Sensitivity, combining the results of these metrics. Specificity signifies the proportion of areas forecasted by the model as non-interest regions to the actual non-interest regions labeled, measuring the ability to judge pixels in non-interest regions. Accuracy denotes the proportion of areas forecasted by the model as interest regions to all areas.

3.3 Image Enhancement Results and Analysis

This paper analyzes the proposed molybdenum target image enhancement algorithm based on gradient information and contrast reconstruction from subjective visual effects and objective evaluation indicators to comprehensively evaluate it. Fig. 3 shows the results under different enhancement operations. Fig. 3(a) is the original image, and Fig. 3(b) is the image reconstructed based on gradient information, where the boundary gradient of the mass is more significant, to some extent overcoming the problem caused by the gradual edge transition characteristics of breast lesions. Fig. 3(c) is the image reconstructed based on contrast, where the contrast between the mass area and the surrounding environment is significantly improved compared to Fig. 3(a) and Fig. 3(b). Figs. 3(d) and 3(e) are images processed by methods from references [33] and [34] respectively. Fig. 3(d) still does not improve the gradual edge transition characteristics, with unclear gradient information. Although Fig. 3(e) enhances the contrast, it does not highlight the gradient information of the edges. Fig. 3(f) shows the image processed using the technique suggested

in this work, which first reconstructs the gradient information and then reconstructs the contrast. This method has more obvious gradient information and dramatically improves the contrast.



(a) Original image (b) Gradient information reconstruction (c) Contrast reconstruction (d) Reference [33] (e) Reference [34] (f) Proposed method

Figure 3: Images under different enhancement operations

Table 2 shows the objective evaluation indicators of three tumor image samples after different enhancement operations. Using the method proposed in this article, the SF and AG indicators of the images processed by the image enhancement algorithm, which includes gradient information reconstruction and contrast reconstruction, are higher than in other cases. This indicates that the edge information of the breast molybdenum target image after processing with the method proposed in this article is more prominent and more transparent.

Alongside advancements in low-level image quality measurements (SF and AG), it is essential to evaluate the effect of the enhancement procedure on segmentation performance. Consequently, an additional study was performed utilizing the U-Net++ network on datasets enhanced by various ways, and the segmentation outcomes were evaluated. Table 2 demonstrates that the dataset augmented by the suggested method attained a Dice coefficient of 96.52%, an IoU of 93.30%, a sensitivity of 96.56%, and an accuracy of 98.84%, surpassing datasets processed solely using gradient or contrast reconstruction, or lacking augmentation. This verifies that the suggested gradient and contrast enhancement method enhances image clarity and substantially increases U-Net++ segmentation accuracy and boundary precision.

Table 2: Comparison of image enhancement evaluation indexes

Sample	Unenhanced		Gradient information reconstruction		Contrast reconstruction		Proposed method	
	SF	AG	SF	AG	SF	AG	SF	AG
1	4.48	2.69	7.40	4.26	8.81	5.32	15.25	8.71
2	5.52	3.35	9.19	5.33	9.96	5.65	20.21	11.14
3	5.09	3.04	9.28	5.31	11.41	6.83	24.47	13.89

Table 3 delineates the segmentation performance of U-Net++ utilizing various input kinds. Both gradient and contrast reconstructions independently enhance Dice, IoU, sensitivity, and accuracy compared to the original pictures, however, the fully upgraded images attain superior performance across all measures. The results validate that the suggested improvement technique not only elevates image quality but also markedly enhances segmentation efficacy.

Table 3: Impact of Image Enhancement on U-Net++ Segmentation Performance

Input Type	Dice (%)	IoU (%)	Sensitivity (%)	Accuracy (%)
Original Images	94.29	89.36	94.89	98.24
Gradient-Reconstructed Images	95.06	90.64	94.62	98.44
Contrast-Reconstructed Images	95.86	92.11	96.04	98.63
Proposed Method (Full)	96.52	93.30	96.56	98.84

To confirm the superiority of the approach introduced in this study, two excellent domestic and foreign studies of the same kind were selected for comparison. Table 4 compares the suggested technique in this work with the techniques in references [33] and [34] concerning objective evaluation indicators for image enhancement and timeliness. It can be seen that the SF and AG indicators of the images processed by the introduced approach in this study are higher than the other two methods, indicating that the suggested approach in this work has certain advantages in comparison with similar domestic and foreign studies.

Table 4: Comparison of evaluation indexes between the suggested approach and similar studies

Method	SF	AG	Time（s）
Reference[33]	12.85	7.10	7.65
Reference[34]	16.02	8.15	72003.25
Proposed method	16.16	8.23	2271.83

*The bolded parts indicate the best results in this experiment.

The timeliness of the three methods was evaluated to more comprehensively and precisely present the usefulness of the suggested approach. Due to the limited number of samples in the DDSM-BCRP subset, this experiment first processed 60 samples before data augmentation. Therefore, the time required to process 60 images using three image enhancement methods is compared. As demonstrated in Table 4, the introduced approach in this work is superior to reference [34] in both timeliness and image enhancement evaluation indicators. Although the introduced technique in this study is inferior to the technique in reference [33] in terms of timeliness, it outperforms that method regarding image enhancement evaluation indicators.

3.4 Image Segmentation Results and Analysis

3.4.1 Comparison of segmentation results under different enhancement operations

Fig. 4 presents the SRs of the U-Net++ network. Fig. 4(a) shows four samples containing breast masses, while Figs. 4(b), 4(c), 4(d), 4(e), 4(f), and 4(g) demonstrate the predicted SRs from the U-Net++ network for the original images of these four samples, the images reconstructed from gradient information, the images reconstructed from contrast, the results from reference [33], the results from reference [34], and the outcomes processed by the approach suggested in this work, respectively. Fig. 4(h) presents the segmentation outcomes achieved by the suggested methodology, alongside samples depicted in Fig. 4(a) and comparative results illustrated in Figs. 4(b) to 4(g). The proposed method combines gradient and contrast enhancements with U-Net++, resulting in enhanced boundary preservation and mass localization relative to baseline techniques, alongside diminished noise and improved structural detail reconstruction.

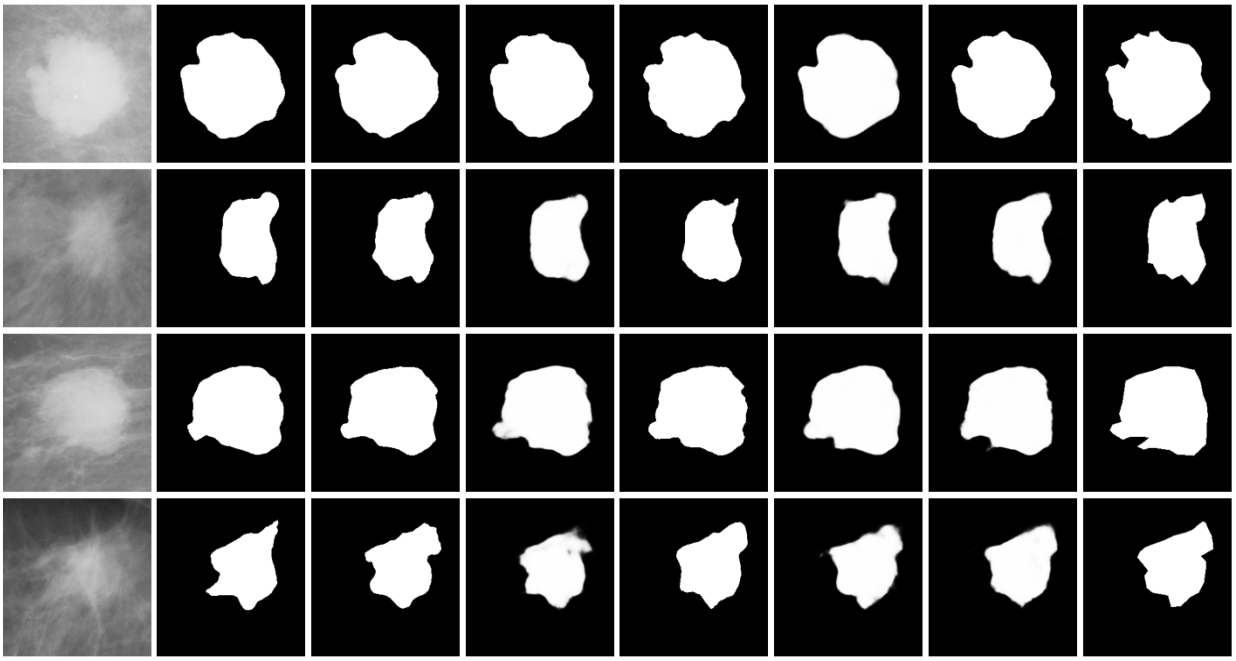
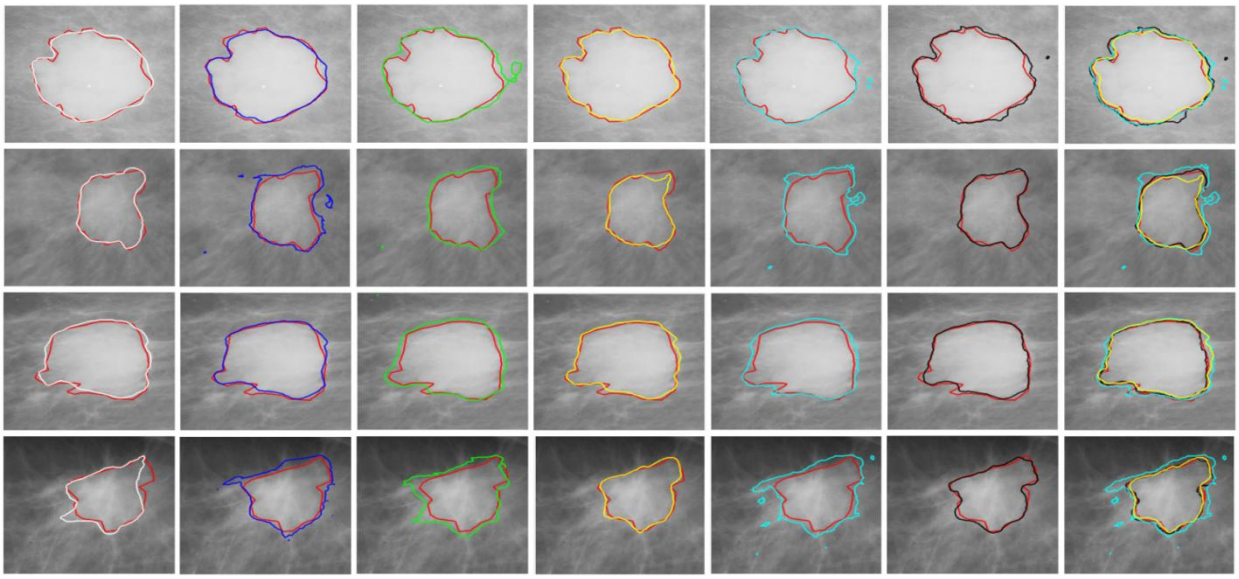


Figure 4: Comparison of U-Net++ network SRs

To make the SRs more intuitive, the network SRs are outlined with closed curves, as demonstrated in Fig. 5. The area inside the red curve denotes the labeled region, the area inside the white curve signifies the SR after inputting the unenhanced image into the U-Net++ network, the area inside the blue curve denotes the SR after inputting the image reconstructed from gradient information into the U-Net++ network, the area inside the green curve signifies the SR after inputting the image reconstructed from contrast into the U-Net++ network, the area inside the yellow curve denotes the SR after inputting the image processed using the method from reference [33] into the U-Net++ network, the area inside the cyan curve represents the SR after inputting the image processed using the method from the reference [34] into the U-Net++ network, and the area inside the black curve represents the SR after inputting the image processed using the strategy put forth into the U-Net++ network. Fig. 5 juxtaposes the segmentation contours derived from six methodologies superimposed over the original mammograms. (a) illustrates U-Net++ applied to original photos, revealing several boundary irregularities. (b) and (c) present outcomes utilizing gradient- and contrast-enhanced inputs, which promote localization but overlook fine structures. Methods (d) and (e) from references [33] and [34] exhibit intermediate performance, with discrepancies in low-contrast regions. (f) introduces the suggested methodology, which integrates gradient and contrast reconstruction, resulting in enhanced boundary precision and a high degree of correspondence with the ground truth.

Fig. 5(g) presents the segmentation contour lines of the approach suggested in this document, as well as those from references [33] and [34], on a single background.



(a)Unenhanced (b) Gradient information reconstruction (c) Contrast reconstruction (d)Reference [33] (e)Reference [34] (f)Proposed method (g)contrast

Figure 5: Comparison of contour lines of U-Net++ network SRs

Through Figs. 4 and 5, it can be visually observed that the segmentation performance of the unenhanced images as the dataset input into the network is unsatisfactory, with the problem of inaccurate edge positioning still quite evident. The SRs of images reconstructed from gradient information as the dataset can better consider edge information and perform well in edge detail recognition. However, the fitting between the segmentation and labeled areas is average. The images reconstructed from contrast as the dataset can better identify the labeled area but perform poorly in recognizing edge detail information.

In the instances depicted in Fig. 5, the segmentation outcomes on the original photos yielded an average Dice score of 94.29%, whereas gradient-reconstructed and contrast-reconstructed inputs enhanced the Dice scores to 95.06% and 95.86%, respectively. The fully upgraded images achieved the highest Dice score of 96.52%, validating that the visual enhancements corresponded with improvements in quantitative segmentation ability.

The overall segmentation performance after processing with the method from reference [33] is good, but compared with the strategy in this work, some SRs have poor edge fitting. The SRs, after processing with the method from the reference [34], have poor fitting between the segmentation area and the labeled area. From Fig. 5(g), it is evident that the black contour line representing the approach suggested in this work fits the red contour line representing the label the best. Therefore, the strategy put forth in this work achieves better outcomes by having a higher distinction in identifying the boundaries of the mass while fully recognizing the labeled area of the mass. Table 5 compares objective evaluation metrics for the segmentation of the U-Net++ network. The image enhancement algorithm in this work, including the reconstruction of gradient information and contrast, outperforms other cases in commonly used pixel-level objective evaluation metrics for MIS.

Table 5: Comparison of segmentation metrics in U-Net++ for the four cases of datasets

Methods	Gradient information reconstruction	Contrast reconstruction	IoU	Precision	Sensitivity	Dice	Specificity	Accuracy
Unenhanced			89.36±0.052	93.98±0.054	94.89±0.030	94.29±0.032	98.89±0.007	98.24±0.009
1	√		90.64±0.045	95.42±0.046	94.62±0.033	95.06±0.027	98.91±0.008	98.44±0.010
2		√	92.11±0.029	95.77±0.026	96.04±0.024	95.86±0.016	99.11±0.007	98.63±0.008
3	√	√	93.30±0.023	96.53±0.020	96.56±0.018	96.52±0.013	99.27±0.005	98.84±0.007

*The bolded parts indicate the optimal outcomes in this test.

To confirm the strategy's advantage concerning segmentation performance, Table 6 provides a comparison

of objective evaluation metrics for image segmentation among the U-Net++ network combined with the approach suggested in this document, the method from reference [34], and the method from reference [35]. It can be seen that the image enhancement algorithm put forth in this work, including the reconstruction of gradient information and contrast, outperforms the other two methods in commonly used pixel-level objective evaluation metrics for MIS.

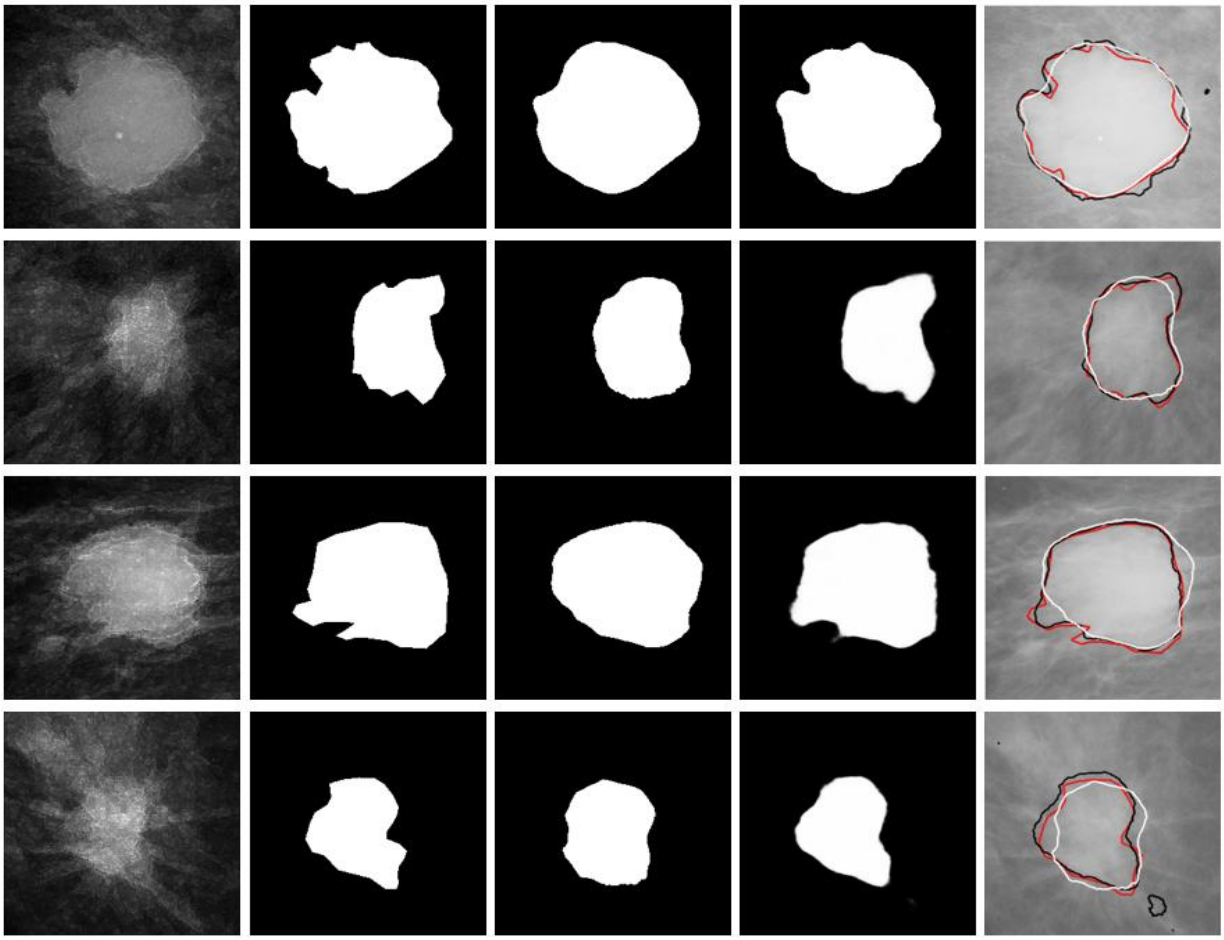
Table 6: Comparison of the suggested technique with similar domestic and foreign studies on the segmentation average index

Methods	IoU	Precision	Sensitivity	Dice	Specificity	Accuracy
Reference**Error! Reference source not found.**	91.72±0.031	95.66±0.029	95.74±0.025	95.65±0.017	99.11±0.006	98.55±0.009
Reference**Error! Reference source not found.**	92.72±0.027	96.36±0.026	96.11±0.020	96.20±0.015	99.18±0.008	98.71±0.009
Proposed method	93.30±0.023	96.53±0.020	96.56±0.018	96.52±0.013	99.27±0.005	98.84±0.007

*The bolded parts indicate the best results in this experiment. To evaluate the reliability of the data, we calculated the mean and standard deviation for each assessment measure over the test folds. Paired t-tests demonstrated statistically substantial enhancements ($p < 0.05$) in Dice and IoU scores when contrasting the suggested strategy with baseline enhancement techniques. The variance in segmentation results was especially pronounced in instances involving small or irregularly shaped masses, or when such masses were situated adjacent to thick glandular tissues. The outlier cases resulted in marginally reduced metric values, underscoring the necessity for more refining in boundary-sensitive situations. To effectively demonstrate the efficacy of the proposed enhancement technique, comparative segmentation outputs are now displayed with uniform labeling across all visual figures. Each figure contains comprehensive captions specifying the input type, segmentation technique, and significant visual observations to enhance clarity and reader understanding. A new summary table has been incorporated to present class-wise segmentation parameters, including Dice coefficient, Intersection over Union (IoU), sensitivity, and specificity, each with 95% confidence intervals. This enhancement facilitates a more comprehensive assessment of the model's efficacy across various lesion types and reinforces the statistical significance and diversity of the findings.

3.4.2 Comparison of segmentation results from different networks

After processing the dataset with the strategy in this work, the data was also fed into the U-Net network for comparison with the SRs of the U-Net++ network. The U-Net++ network is an improvement based on the U-Net, with a more flexible feature fusion method and lower training time cost. The comparison of SRs is demonstrated in Fig. 6. Fig. 6(a) demonstrates four images containing breast mass samples processed by the enhancement algorithm proposed in this paper. Fig. 6(b) shows the corresponding label images of the samples. In contrast, Figs. 6(c) and 6(d) show the SRs in U-Net and U-Net++, respectively. In Fig. 6(e), the area within the red curve signifies the label, the white curve represents the SR of the U-Net network, and the area within the black curve represents the SR of the U-Net++ network.



(a)Proposed method (b) label image (c) U-Net (d) U-Net++ (e)contrast

Figure 6: Comparison of different network SRs

Through Fig. 6(c) and Fig. 6(d), it is visually observed that compared to the SRs forecasted by the U-Net++ network model, the SRs forecasted by the U-Net network model have poorer recognition of the edge details of the mass cannot fit the contour of the mass well, and fail to obtain practical segmentation areas. Fig. 6(e) more intuitively reflects the fitting degree of the SRs, with the fitting degree of the black curve and the red curve much higher than that of the white and red curves. Therefore, the segmentation performance of the U-Net++ network is superior to that of the U-Net network.

Table 7 presents the evaluation metrics of U-Net and the approach suggested in this work (U-Net++) under the image enhancement algorithm proposed in this paper. The approach's segmentation performance has been notably boosted in comparison with the U-Net network model.

Table 7: Comparison of segmentation evaluation metrics of the enhancement algorithm suggested in this study on different models

	IoU	Precision	Sensitivity	Dice	Specificity	Accuracy
Proposed enhancement method+U-Net	66.35	74.09	89.20	77.91	93.16	92.21
Proposed method	93.30	96.53	96.56	96.52	99.27	98.84

*The bolded parts indicate the optimal outcomes in this test.

Table 8 provides the segmentation evaluation metrics of breast molybdenum target images for different network models, including U-Net, FCN with attention mechanism and dense connections, U-Net mixed with the enhancement algorithm suggested in this work, end-to-end network model, U-Net++, and U-Net++ combined with the enhancement algorithm proposed in this study. The evaluation metrics incorporate specificity, sensitivity, Dice coefficient, and accuracy.

Table 8: Comparison of evaluation indexes under various network models

Method	Sensitivity	Dice	Specificity	Accuracy

Reference**Error! Reference source not found.**	77.89	82.24	84.69	78.38
Proposed enhancement method+U-Net	89.20	77.91	93.16	92.21
Reference**Error! Reference source not found.**	80.30	85.08	99.76	98.91
U-Net++	94.89	94.29	98.89	98.24
Proposed method	96.56	96.52	99.27	98.84

*The bolded parts show the optimal results in this test.

Table 8 shows that the Dice coefficient and sensitivity, the segmentation performance of feeding the dataset processed by the image enhancement algorithm proposed in this paper, which includes gradient information reconstruction and contrast reconstruction, into the U-Net++ network is superior to additional network structures. However, regarding specificity and accuracy, the method introduced in this document is slightly inferior to the end-to-end network suggested in the reference [36]. Still, the difference is minimal, with a margin of 0.49 % points and 0.07 % points, respectively. However, the sensitivity and Dice coefficient are much higher than the end-to-end network, with margins of 16.26 percentage points and 11.44 percentage points, respectively.

These applications described in this article target the segmentation of masses in the breast on mammograms, which will boost the precision and dependability of CAD systems in medical images. The proposed image-enhancing algorithm, considering both gradient and contrast reconstruction, may be used as a preprocessing method for the mammographic pictures so that the boundary of lesions could be heightened and interference from noise could be reduced. It can be easily implemented in clinical practice to enable radiologists to obtain accurate segmentations of breast masses using up-to-date DL models, namely U-Net++. Moreover, its efficiency, tested with a five-fold cross-validation, facilitates straightforward generalization on other medical image data, including lung nodules and brain tumors. Critical limitations include the fact that this approach is based on a small dataset, the poor adaptiveness of significant and diverse populations, and the different situations in image acquisition that could be foreseen. Regarding computational complexity, high-performance hardware may be required in the enhancement and segmentation process. Limitations that future work may want to deal with include investigating ways of data augmentation and algorithm optimization for real-time and scalable deployment. In addition to segmentation performance, the proposed enhancement and segmentation pipeline needed an average CPU execution time of 0.011325 seconds per image. Memory utilization throughout model inference remained below 1.2 GB, suggesting that the technique is computationally efficient and suited for real-time or clinical application. To assess the contribution of each enhancement component, we performed an ablation study. Using gradient-only input improved Dice from 94.29% to 95.06%, and contrast-only inputs yielded 95.86%. When combined, the proposed method achieved 96.52%, confirming the complementary benefits of both enhancements.

3.5 Discussion

The suggested method was assessed in comparison to other state-of-the-art (SOTA) techniques, including ACA-ATRUNet [17], CNN-based classifiers [19], and enhancement-driven U-Net variations [25]. In comparison to existing models, our improved U-Net++ architecture attained superior segmentation performance across all critical parameters, including Dice (96.52%), IoU (93.30%), and Sensitivity (96.56%). The improvements can be ascribed to two main innovations: (1) the reconstruction of gradient and contrast information before segmentation, enhancing edge clarity and mass delineation, and (2) the linear fusion of structural and edge information, which more effectively maintained lesion boundaries compared to raw input or contrast-only preprocessing.

In contrast to existing methods that depend exclusively on raw pictures or generic denoising techniques, our approach specifically targets the distinct attributes of mammograms, including low contrast and glandular tissue interference, by amplifying low-frequency features and refining edge gradients.

Nonetheless, several segmentation inaccuracies were still noted, especially in instances involving small, irregularly shaped masses or those situated near dense glandular structures. In some instances, the gradient transitions were less distinct, and the adjacent textures occasionally perplexed the model. These problems indicate that the integration of shape priors or adaptive attention techniques may enhance performance in subsequent iterations.

4 Conclusion

This paper focuses on the subjects introduced in the segmentation and analysis by the gradual edge transitions of masses and low contrast in breast mammography images. This study researched several typical segmentation networks in performance by DL integrated with CAD and evaluated different preprocessing methods for their impact on the SR. The significant contribution of the paper is that it proposes an image enhancement algorithm that combines the reconstruction of gradient information with contrast reconstruction to improve the clarity and boundary definition of masses while suppressing noise interference.

Compared with state-of-the-art works at home and abroad through large-scale experiments, the proposed algorithm exhibited significant improvements in segmentation performance, outperforming the existing

algorithms in accuracy, sensitivity, and Dice coefficient. Such improvement indicates that the preprocessing enhancement has much potential to boost DL networks for medical image analysis. Future studies will concentrate on the following two significant tasks: maximization of the limited medical image datasets through specific strategies, namely data augmentation and transfer learning, and further enhancing the proposed algorithm's generalization ability for other medical imaging using more datasets, namely lung nodules and brain tumors. Various directions are realized in clinical practice by optimizing the computation efficiency and checking its applicability on more practical and prevalent CAD systems. This could allow further adjustment according to the collaborating radiologists and clinicians' practical clinical experience to refine the operation of the suggested strategy in actual healthcare practice.

The changes not only enhanced the visual clarity of mammographic pictures but also resulted in a quantifiable increase in segmentation accuracy, with the Dice coefficient attaining 96.52% and IoU 93.30% utilizing the U-Net++ model. This study concentrated on breast mass segmentation; however, the methodology rooted in structural preservation and edge enhancement may apply to other areas in medical imaging, including brain tumor segmentation in MRI and lung nodule detection in CT scans. Future research will investigate its adaptability and generalizability across many imaging modalities and datasets.

Nomenclature

Abbreviations			
ACA-AMDN	Attention-Constrained Adaptive-Multidimensional Network	CF	Column Frequency
ACA-ATRUNet	Attention-Constrained Adaptive Atrous U-Net	D	Dictionary matrix
AUC	Area Under the Curve	$F1$	The harmonic means of Precision and Sensitivity
Bi-ConvLSTM	Bidirectional Convolutional Long Short-Term Memory	FN	False Negatives
BUSI	Breast Ultrasound Images	FP	False Positives
CAD	Computer-Aided Diagnosis	H	the total variation of the structural component
CLAHE	Contrast Limited Adaptive Histogram Equalization	I	the input image
CNN	Convolutional Neural Network	K	the inherent variation
DDSM	Digital Database for Screening Mammography	L	Sparsity constraint parameter
EME	Enhancement Measure Estimation	M	Height (number of rows) of the image
FCN	Fully Convolutional Network	N	Width (number of columns) of the image.
IoU	Intersection over Union	RF	Row Frequency
K-SVD	K-Singular Value Decomposition	SF	Spatial Frequency
MIAS	Mammographic Image Analysis Society	TN	True Negatives
MML-EOO	Multi-Model Learning Optimization for Enhanced Output Optimization	TP	True Positives
PCA	Principal Component Analysis	X	Encoding vector
ROI	Region of Interest	Y	Matrix of given samples
SVM	Support Vector Machine	Subscripts	
UDIA	Ultrasonography Dataset for Imaging and Analysis	p	Index of a pixel in the 2D image
USM	Unsharp Masking	q	Index of a pixel within a square region
BCRP	Breast Cancer Resistance Protein	x	directions of the pixels
WU-Net++	Weighted U-Net++ model	y	directions of the pixels
symbol		Greek symbol	
AG	Average Gradient	γ	grayscale levels

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No competing interests are disclosed by the authors.

Authorship Contribution Statement

Miao GUO: Supervision, Writing-Original draft preparation, Conceptualization, Project administration.
Ating YANG: Methodology, Software
Min DONG: Language review

Data Availability

The authors will provide unrestricted access to the raw data that was used to support this article's conclusions.

Declarations

Not applicable.

Conflicts of Interest

The scholars claimed no conflicts of interest considering this investigation."

Author Statement

All of the writers have read and approved the manuscript. Each author feels that it is honest and that the authorship requirements have been fulfilled, as previously mentioned in this document.

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No research involving humans or animals is included in this investigation.

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CNN-SVM-based Human-Computer Interaction Model for Automotive Systems in Complex Driving Environments

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In the complex driving environment, with the increase of task difficulty, the change of diversity and relevance, the phenomenon of perceptual mode conflict, strong cognition or increased difficulty of operation appears when drivers deal with tasks, which affects the execution of primary and secondary tasks. The information expressed and transmitted by multimedia technology is real-time, and only with real-time can we interact and transmit information with users. This paper discusses the design of automobile man-machine interaction based on multimedia information acquisition technology in complex driving environment. Based on users' situational awareness, this paper studies users' interactive needs and experiences in different driving situations, and proposes CNN-SVM (Convolutional Neural Network-support vector machine) emotional perception model. After automatically extracting spectral features through CNN, support vector machine (SVM) is used instead of traditional Softmax classifier to achieve accurate classification of multi class emotions. The experiment focuses on identifying the following core emotion categories: Anger, Neutral, Joy, and Anxiety, and verifies the model's generalization ability in driving scenarios through cross validation. In the spectrum segmentation experiment, the same network structure as CNN Net was used, and SVM was used instead of softmax classifier. CNN Net was used for training each time. After training, use the test sample set to calculate the input features of the softmax classifier, and input the new features into SVM to calculate the classification result of CNN-SVM. Select 500 test set images from the CityScapes dataset for testing, with MIoU (Mean Intersection Point on Consortium) used as the testing metric. The experimental results show that the model has improved the segmentation accuracy of roads, sidewalks, buildings, etc. Compared with several mainstream segmentation algorithms currently available, this algorithm has relatively small improvements for smaller target objects such as lights, signs, vegetables, and riders, with improvements of 1%, 0.5%, and 0.9%, respectively. In driving scenarios, users' judgment of "safety" mainly depends on whether secondary tasks occupy the cognitive and interactive channels of the primary driving task. This article explores how avoiding these two factors can provide users with a sense of security and improve their interaction experience.

Povzetek: Predstavljen je model zaznave čustev CNN-SVM za avtomobilske sisteme, ki v kompleksnih voznih okoljih izboljša interakcijo človek-stroj z natančnejšim prepoznavanjem govornih signalov in uporabniških stanj.

1 Introduction

With the wide application of computer technology and network technology in the field of transportation and the continuous development of on-board technology, revolutionary changes are taking place in the internal space of cars, human-machine interface operation and interaction process. At present, the vehicle interior information model is evolving from a single vehicle state information model to a complex information system. Improving the corporate image of its own brand by providing high-quality products has always been the direction of efforts and exploration. Improving the user experience during the use of automobile products is an important aspect of the project. In order to achieve effective control of vehicles, people and machines must cooperate in depth in perception, decision-making and execution, share vehicle control and decision-making power, and cooperate to complete driving tasks. The core problem of human-computer co driving is still the coordination of human-computer interaction. Due to the non-repeatability of autonomous driving testing scenarios and the limitations of safety, cycle, and cost of testing, it is difficult to rely solely on real vehicle road testing experiments for related technical testing. With the progress of simulation technology, the relevant tests of autonomous vehicle can be carried out in a safer, more

comfortable and more economical environment. As a vehicle test tool, the driving simulation system takes into account the data acquisition functions of the vehicle end and the human factor end. Using simulation technology to realize high-precision restoration of multiple scenes greatly improves the efficiency of human-computer interaction test and evaluation of intelligent vehicles. It has important practical value and significance for the research of intelligent vehicle human-machine co driving technology.

Traditional human-computer interaction research emphasizes "task ability matching", but intelligent vehicles need to further optimize the dynamic balance of "cognitive load attention resources". Predicting driver distraction risk through voice emotion perception and automatically reducing information density on the central control screen. Gesture recognition (such as steering wheel touch/head up display gestures) needs to be coordinated with voice interaction to avoid "modal conflicts" (such as conflicts between voice commands and gesture intentions). The accuracy of camera gesture recognition decreases by more than 30% in strong light/rainy and snowy weather [citation]; Complex gestures (such as 3D spatial gestures) have high learning costs and can easily cause driver anxiety. Voice emotion perception can predict users' acceptance of gesture interaction (such as automatically switching to voice priority mode in an "angry" state). Focus more on task efficiency in static scenarios (such as laboratory environments) and ignore emotional interference in dynamic driving scenarios. In recent years, with the wide application of information technology, intelligent system and network technology in the field of vehicles and the development of on-board information technology, the interior space, man-machine interface, operation and interaction process of automobiles are undergoing revolutionary changes, and the control interface is undergoing essential changes. This change improves the mobility and comfort of drivers, and also increases the risk and danger level of drivers' poor performance of vehicle control tasks [1]. The biggest feature of multimedia information collection technology is that non-intuitive multi-source data information can be intuitively expressed and transmitted to users, and information transmission and communication can be realized by stimulating users' sensory awareness. In fact, multimedia information collection technology uses computer to realize information exchange and transmission with users, which is essentially a man-machine interaction technology. With the improvement of drivers' requirements for car comfort and safety, the traditional in-vehicle network technology is no longer fully competent. Therefore, the core of car man-machine interaction design is based on in-vehicle technical equipment, which provides drivers with a good interactive way to cope with complex driving environment and improve driving experience.

2 Related work

At present, the information model inside the automobile has gradually developed from a single driving and vehicle condition information model to a complex information system including vehicle information, inter-vehicle information, and information of interaction between vehicles and other information carriers [2, 3]. Research on automotive ergonomics started in 1950 s, and a lot of surveying and mapping analysis and basic research work have been done. Especially in developed countries, they attach great importance to the ergonomics factors in automobile development. Krishan et al. put forward the modeling and optimization research of human upper limb posture of automobile man-machine interface, aiming at the matching analysis needs of automobile man-machine interface design [4]. As autonomous driving technology evolves towards L4/L5 levels, the limitations of single sensors or deterministic algorithms in complex dynamic scenarios are becoming increasingly prominent. Gao et al. [5] provided a systematic review of intelligent vehicle autonomous driving tracking technology based on fuzzy information processing and multi-sensor fusion. Focus on analyzing its collaborative mechanism in modeling environmental perception uncertainty, spatiotemporal alignment of multimodal data, and dynamic decision optimization. Yang et al. extracted the rotation invariance feature of hand, and used Fourier operator, edge histogram and boundary moment invariants as the basis of pattern recognition [6]. Ji et al. have implemented a virtual environment system, which is mainly used in large-scale biological modeling. Gestures are used as inputs to control devices in the virtual environment, which provides an interactive interface for biological modeling [7]. Chen and Jia think that the virtual assistant of information system in human-computer interaction of electric steam is helpful to improve users' emotional experience, establish trust mechanism and emotional communication between users and the system, and contribute to the establishment of information system model [8]. Fang and Wang user-centered user experience design by collecting user information, refining user requirements, simulating user scenarios, real-time user testing and feedback has become the goal and purpose of human-machine interface design [9]. Huang et al. used CNN and short-term and long-term memory architecture to study end-to-end unmanned driving, and directly controlled the direction of the vehicle [10]. Wang et al. used the top-down structure to combine low-resolution features with high-resolution features, and built a feature pyramid with similar semantic level, which improved the effect of multi-scale object detection [11].

In the case of human-computer interaction, besides ensuring driving safety, driving pays more attention to getting a good interactive experience in the process of human-vehicle interaction. Experience is a typical emotional element, and it is a higher level of experience in cognitive level. In complex driving environment, with the increase of task difficulty, the change of diversity and relevance, the phenomenon of perceptual mode conflict, strong cognition or increased difficulty of operation appears when drivers deal with tasks, which affects the execution of primary and secondary tasks [12]. The information expressed and transmitted by multimedia technology is real-time, and only with real-time can we interact and transmit information with users. Real-time is

mainly manifested in the fact that when multimedia information collection technology interacts with users, multiple kinds of information interact synchronously under multiple sensory stimuli. This paper discusses the design of automobile man-machine interaction based on multimedia information acquisition technology in complex driving environment. Based on users' situational awareness, it is of great guiding significance to study users' interactive needs and experiences in different driving situations, to construct the theoretical framework of in-vehicle human-computer interaction design of intelligent cars, and to propose appropriate design methods.

The key factors of interaction design include visual experience. Buttons of different types of functions are designed in different shapes and sizes. And distinguish the main task from the secondary task in a guiding manner, so as to quickly identify and process the main task. Secondly, auditory experience. In the on-board environment, voice control interaction is considered to be the most convenient human-computer interaction mode with the least impact on driving. Tactile experience. In the design of central control information entertainment products, human tactile characteristics should be considered and appropriate vibration tactile reminders should be used. It can provide tactile sensation for blind operators during driving, and minimize operations that must rely on visual assistance. Although current research has made some progress in the field of automotive human-computer interaction, such as basic research in automotive ergonomics, gesture recognition, user experience design, autonomous driving visual processing, and multi-scale object detection, it mostly focuses on optimizing single dimensions or local functions, and there is relatively little systematic research based on multimedia information collection technology in complex driving environments to comprehensively integrate visual, auditory, tactile and other sensory experiences for user situational perception. There are gaps in the existing research on multimodal interaction synergy and interaction design theoretical frameworks that dynamically adapt to different driving scenarios. The solution proposed in this article aims to fill this research gap by constructing a theoretical framework for intelligent car human-machine interaction design based on user context perception, and proposing a multi-sensory interaction design method that adapts to complex driving environments to enhance user interaction experience and driving safety, Table 1 is the summary table of existing methods.

Table 1: Summary table of existing methods

Method Type	Algorithm method	Evaluation indicators	Benchmark test dataset	Performance	Main limitations
Traditional HCI methods	Threshold method, template matching	Accuracy, precision, recall rate	Self-built dataset (small-scale)	Accuracy: 70% -80%	Relying on artificial feature engineering, poor generalization ability; Difficult to handle complex motion patterns such as jumping and going up and down stairs.
Machine learning methods	SVM, random forest	Accuracy, F1 score	UCI HAR, WISDM	Accuracy: 85% -90%	Feature extraction requires domain knowledge and is difficult to capture high-dimensional nonlinear relationships; Sensitive to data noise.
Deep learning methods	CNN, LSTM, CNN-LSTM hybrid model	Accuracy, precision, recall rate MIoU	UCI HAR, WISDM, Self-built large-scale dataset	Accuracy: 90% -95%	High demand for computing resources; Some models have poor classification performance for short-term movements such as jumping.
SOTA method	Attention mechanism CNN, Transformer	Accuracy, precision, recall rate MIoU	PUSH (Large Scale Gym Exercise Dataset)	Accuracy: 92.1% (50 categories)	High model complexity and slow inference speed; The classification performance of small sample motion categories (such as rare motion) decreases.

3 Research method

3.1 Situational awareness and human-computer interaction of intelligent automobile

Automobile human-computer interaction design, such as the central control frame layout of Audi A8. The left shortcut menu can switch applications on any interface, and the right application menu can be switched by sliding left and right. The structure of the application menu is clearer than before. The icon adopts an easy-to-understand pseudo object style and combines Audi's brand elements to increase the overall design sense of the icon. Interactive feedback mode adds design highlights. For example, if you touch without pressing the icon on the screen, the icon will be displayed in the form of micro animation. Which increases driving pleasure. Situational awareness involves the knowledge of cognitive science and psychology, which refers to the user's perception and cognition of the situation. Situational awareness enables users to perceive the current environment, understand its meaning and predict the future situation, and make behavioral decisions based on the cognitive results of the current situation. Situational awareness is an individual's conscious dynamic reflection of the environment, which reflects the past, present, future and potential characteristics of the environment. Individuals form a psychological cognitive model of the external environment [13, 14]. The cognitive result of the current situation is the premise for users to make decisions and perform actions, and the main source of users' situational awareness is their perception and understanding of the elements of the current situation and their prediction of the future situation.

Traditional man-vehicle interaction is mainly based on the interaction of steering wheel, physical buttons and other related devices (such as steering control lever). The driving environment is relatively complicated, especially at the auditory level. Words are easily blurred by other words, special tone signals are easily masked by other similar tone signals, and most words are incompatible with each other. In a complex driving environment, drivers interact with the equipment in the car to complete various tasks. In order to clearly and intuitively present the task flow and grasp the details and key points of the task, it is necessary to conduct a structured analysis of the task [15]. Therefore, in order to achieve a faster and better development of multimedia information collection technology, we should combine the current development trend of software technology, cloud technology and big data to realize intelligent functions such as cloud storage and data mining of multimedia information collection technology, which can greatly promote the efficiency and effect of multimedia information collection technology in information expression, transmission and human-computer interaction. Situation Awareness (SA), as the core ability of drivers to dynamically perceive the driving environment, directly affects the input data quality, decision logic, and output reliability of human-computer interaction models (such as CNN-SVM emotion perception model). Drivers may lose key data due to distraction or environmental obstruction (such as no GPS signal in the tunnel). By using the CNN-SVM model for multimodal fusion (combining camera and millimeter wave radar data), the impact of single sensor noise can be reduced, resulting in improved accuracy in target recognition.

Because the human body is a unified whole, the depth information in space is continuous. Therefore, the depth histogram always obeys a specific distribution. There is a gap between the depth value of human body in space and the depth value of background. Therefore, the area that constantly searches for the non-zero depth plane to the zero depth plane is the candidate area of human body. The features extracted by static gesture recognition mainly include low-level geometric features (points, lines, faces, angles) and high-level combination features of the hand.

The number of feature descriptors is k, that is, after selecting k -dimensional data samples, Mahalanobis distance is used to classify features. Mahalanobis distance is a measure of the covariance of the data space, which is a method of "twisting and stretching" the data space and then measuring it [16]. Mahalanobis Distance can adaptively adjust the importance of different dimensions by considering the covariance relationship between features, and in most cases, it is superior to Euclidean Distance and Cosine Distance, as shown in (1).

$$D=(x,y)=\sqrt{(x,y)^{T}\sum^{-1}(x,y)} \tag{1}$$

Where $\sum^{-1}$ is the inverse matrix of covariance matrix.

User's behavioral psychology reflects the process in which users make decisions on current tasks by using existing experience and external rules. Users use their left and right brains to make a decision together, in which the left brain is responsible for logic and rationality, while the right brain is responsible for creativity and emotion [17]. Judging users need to collect information and all possibilities when facing tasks, so they often take a long time to make decisions. Generally, perceptual users will make actions immediately according to the status of the current task, which won't delay too much time.

The purpose of endpoint detection is to detect the actual and effective speech part from the speech signal input to the computer, which plays a very important role in speech recognition. It can not only reduce the calculation of acoustic model training in the recognition process, but also have a positive impact on the recognition accuracy of the speech recognition system.

Let the short-term energy of the n th frame speech signal $x_n(m)$ be represented by E_n, and the calculation formula is (2):

$$E_n=\sum_{m=0}^{N-1}\left|x_n(m)\right|^{2} \tag{2}$$

The reason why short-term energy can be used to judge actual speech and noise is that the energy of noise is less than that of actual speech.

Image feature extraction will be affected by quantum noise and image stains, so the algorithm takes into account the elimination of noise and image stains when extracting contour features. The origin $O(x_0, y_0)$ and the point set $P_l(x_l, y_l)$ in the obtained polar coordinate (r, θ) are respectively converted into points of rectangular coordinate system (x, y), as shown in (3) and (4).

$$x_l = r_l^n \cdot \cos\theta_l + x_0 \tag{3}$$

$$y_l = r_l^n \cdot \sin\theta_l + y_0 \tag{4}$$

Where $\theta_l = l \cdot \Phi, r_l^n$ is the value of normalized r_l .

In digital images, the above conditions can undoubtedly be met. Because the linear gray level transformation of the region will affect the moment characteristics; In order to describe the shape characteristics of the target, the influence of linear gray scale transformation can be eliminated by operating on the binary target area.

Let $\{I(x, y), x, y = 0,1,\cdots, N-1\}$ be a regional binary image or a suppressed background image, then its $(p+q)$-order statistical moment is defined as (5):

$$m_{pq} = \sum_{x=1}^{n}\sum_{y=1}^{n} I(x, y)x^p y^q \tag{5}$$

p corresponds to the moment in the x dimension, q corresponds to the moment in the y dimension, and the order represents the index of the corresponding part.

In image processing, the similarity between individuals can be judged by a variety of measurements. The most representative of these measurement methods is distance measurement (6):

$$d_{ij} = \sum_{i=1}^{K} \left| x_i^l - x_j^l \right| \tag{6}$$

In which, the dimension vector of the object i is represented by x_i , and each element of the vector is represented by $x_i^l (l = 1,2,\cdots, K)$.

Select the binary code string uniquely generated by n point pairs (x, y), which are selected according to certain rules in the $S \times S$ area, such as (7):

$$f_n(p) = \sum_{1 \le i \le n} 2^{i-1} \tau(p; x_i, y_i) \tag{7}$$

$f_n(p)$ in the above formula is a descriptor. n is often weighed according to different application scenarios.

Situational awareness is essentially the user's perception, understanding and prediction of the interactive environment and its future development. Different situational factors will affect people's cognitive results and lead to different behaviors [18, 19]. The situation of users includes interpersonal behaviors, and the research process includes users' psychological cognition and interactive behaviors. Environment mainly refers to the current usage scene, and also includes some external objective environmental factors, such as light, weather, etc.

Understanding users' situational awareness and the influencing factors of the formation of situational awareness, based on users' cognitive characteristics, and putting forward reasonable design strategies for the purpose of improving users' cognitive level and interaction efficiency can improve users' interaction experience in automobile man-machine interaction.

3.2 Design of emotion perception model of human-computer interaction in automobile

An important requirement of human-computer interaction technology is that information interaction and feedback must be real-time. Real-time means that when users interact with computers or other information output devices, they should be able to understand users' intentions and give feedback quickly to realize interactive transmission. Multimedia information collection technology is to express, transmit and interact all kinds of data and information resources in a unified way, so all kinds of information data must have good coordination to ensure the smooth implementation of information interaction [20, 21]. Therefore, at present, the sound control of vehicle information system mainly focuses on the sound command based on navigation system. The biggest advantage of navigation lies in its limited geographical location information, and its language information format is relatively simple. To design a complete human-computer interaction system, we must consider three factors: human factors, system equipment factors and interactive environment factors. Such as sound, tactile devices, visual input and output devices, etc. Interactive factors refer to the core of interactive functions, such as system software.

In the interface design of automobile cab, the ergonomic interface elements used in the display device design are the most complex and diverse, and the types of information carried in the display device are diverse and complicated. With the continuous innovation and development of multimedia technology in the car, the information that drivers need to deal with while driving is becoming more and more diversified, which obviously will inevitably increase certain potential safety hazards. In general, when designing the display device, the operator is required to have a good central vision and to be able to achieve normal peripheral vision. For the driver, it is necessary to concentrate his energy in the process of driving. At this time, if there are many kinds of information for the driver to process at the same time, it will bring some potential safety hazards.

The traditional speech emotion perception model is mainly divided into several schools, one is the traditional school of manual features+machine learning classifier, and the other is the neural network school based on manual features+neural network classification. Compared with existing HCI emotion recognition models, the CNN-SVM model has significant advantages in feature extraction ability, generalization performance, multimodal fusion

potential, and real-time optimization. The CNN-SVM model can control the generalization error within 8% through transfer learning (such as pre training based on ImageNet), making it suitable for cross-cultural and cross linguistic emotion recognition tasks. For example, in vehicle localization, the accuracy of the model's recognition of unseen driving scenarios (such as nighttime and rainy days) decreases slightly. The accuracy of traditional HCI models decreases by about 30% in cross dataset testing, and they are sensitive to complex scenes such as lighting changes and occlusions. For example, in vehicle localization, traditional models have poor robustness in recognizing small targets such as traffic signs. In this paper, a CNN-SVM (Convolutional Neural Network-support vector machine) emotion perception model is proposed. The input is the spectrogram of audio, and the feature is extracted automatically by CNN structure, then the extracted features are input into a multivariate SVM for classification, and then the results are output. The detailed structure of the network model is shown in Figure 1.

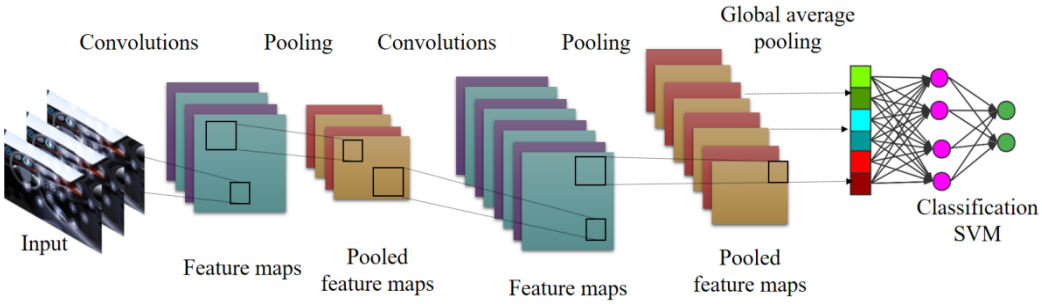


Figure 1: CNN-SVM emotion perception model process

The CNN feature extraction layer adjusts the gradient descent stability by learning rate and batch size to avoid overfitting or slow convergence. The SVM classification layer optimizes the inter class separability of high-dimensional feature space through kernel function selection, improving the recognition accuracy of complex emotional patterns. By introducing attention mechanisms such as CBAM to enhance CNN's ability to focus on time-frequency features of spectrograms. Multi modal inputs, such as combining text transcription with audio features, can be explored to enhance the robustness of emotion recognition. Endpoint detection generally adopts double threshold detection method based on zero-crossing rate and short-time energy. This is because speech signals are generally composed of unvoiced, unvoiced and voiced segments. The silent segment belongs to the background segment, and its average energy is the lowest. Let the voice sampling value at time n be $x(n)$, and the result after pre-emphasis processing is (8):

$$y(n) = x(n) - ax(n-1) \tag{8}$$

Softmax classifier is mainly used in the field of multivariate classification, although traditional binary classification can also be carried out by using multiple binary classifiers to classify and then get the best results. The calculation process of softmax (9):

$$y_i = \frac{e^{x_i}}{\sum_i^m e^{x_i}} \tag{9}$$

For the classification of multi-labels, we should still use binary classifier to carry out multiple groups of experiments, and select the first few with the highest probability.

The speech process of people's speech formation is a double random process, because it is impossible for each speech frame to correspond to a different state, and then the whole speech signal will get a bunch of states. There are as many states as there are speech frames, and whether it is the same person's pronunciation in different time periods or different people's pronunciation, different speech signals will be produced, which are quite different from each other. Therefore, in fact, each state will correspond to multiple adjacent speech frames, which is reasonable because each frame is very short.

If the excitation function is sigmoid nonlinear function, the neuron output is shown in the following (10):

$$f(x) = \frac{1}{1+e^{-x}} \tag{10}$$

Assume that there is a pile of original data, that is, training sample sets, and then build a neural network. Firstly, initialize its weight parameters, and then iteratively train its weight parameters through these training sample sets.

To solve the problems mentioned above, batch gradient descent method is generally adopted. Firstly, the weight parameter matrix w is randomly initialized, and then it is updated by iterative training of the following (11):

$$w_{jk}^{l} := w_{jk}^{l} - \eta \frac{\partial C}{\partial w_{jk}^{l}} \tag{11}$$

$:=$ is the assignment operation, η is the learning rate, and $\frac{\partial C}{\partial w_{jk}^{l}}$ is the partial derivative of the loss function C to the weight coefficient of the k th neuron in the l layer.

3.3 Analysis of interface information in different task situations and user categories

Automobile control equipment refers to the equipment that can change the running state of automobile through functional operation. The rationality of the design of vehicle control equipment directly affects the working efficiency of the whole human-vehicle operating system. In the traditional driving process, the driver's hand can't leave the steering wheel, and it needs to meet other vehicle operating functions and ensure the driver's operating comfort. From the perspective of location and form, the location of the future human-computer interaction graphical interface is no longer limited to the driver's seat, but integrated in the roof, window, etc. The graphical interface is presented through projection, holography, electronic grid, intelligent physical surface, light and other technologies. Future concept vehicles will create interactive fun for users on the basis of emphasizing adaptation to human-machine engineering. At the behavioral level, the current concept car introduces more "black technology", and makes more innovations in human-computer interaction from the perspective of adapting to human-computer engineering and perception. The emotional design of intelligent mobile space in the future needs to integrate the current fragmented functions based on these innovations. From the unified interface such as the on-board steward to the user, the output of the function and interaction layer can improve the efficiency of human-computer cooperation and cultivate the user's emotion.

Central control display is often used for vehicle information display, multimedia display and control, electronic navigation display, etc. Especially, with the increase of all kinds of automobile automation technology, the functions of traditional central control area become more and more complicated, and it becomes more and more difficult to operate by physical keys and the learning cost is higher and higher. Digital display uses digital technology to directly display relevant parameters. The observer's reading of data information is relatively simple and intuitive, and has high accuracy, but it can't give people a vivid image, which makes information reading lack a concept of "degree". At present, two kinds of information display methods are commonly used in automobile instruments.

The driving information area mainly displays vehicle information during driving and parking, such as vehicle road information, vehicle speed, electric quantity information, vehicle body equipment information, etc. The function control area is mainly the detailed control area after the user enters the function of "no words" through function navigation, and the content of this area changes according to the user entering different functions. According to the analysis of users' characteristics and behaviors, based on the functional requirements in the current scene, low-level interaction mode is used in the design of intelligent electric vehicle's on-board central control man-machine interaction information interface to reduce users' learning and use costs, and provide customizable content, so as to reduce the learning cost of primary users, improve the fluency of intermediate users, and increase the available space for expert users.

In the driving situation, the user's judgment of "safety" mainly depends on whether the secondary task occupies the cognitive channel and the interactive channel of the main driving task. By avoiding the two, the user can be given a sense of security and the interactive experience can be improved. In the automatic driving situation, the driver basically does not undertake the driving task and driving load, and the application characteristics of various kinds of interactive control methods are basically consistent with those of manual driving situation and auxiliary driving situation. At this time, the consideration of interaction design should be mainly based on the target customers. Based on the perception and judgment of the current road conditions, the system puts forward the warning of dangerous driving or collision, which can inform users to respond in advance, and even actively avoid it through its lane keeping system, which greatly improves the driving safety.

The previous research work on vehicle location and recognition can be roughly divided into two parts: locating and recognizing vehicles in static images and locating and recognizing vehicles in video sequences. The main difference between them is that video can use dynamic information, while static images have less prior knowledge. Whether a practical vehicle positioning and recognition application system has good positioning and recognition performance is of course mainly determined by the performance of the core algorithm model, but it also depends on the design of the system to a certain extent. The number of car frames is determined by the difference pictures, and the gray values in the row and column directions of the processed difference pictures are statistically analyzed. And the reusable image of the frame boundary and the image pixel coordinate position is obtained according to the judgment result of the number of frames. The actual position and size of the vehicle can be obtained through the coordinate correspondence to realize the recognition and positioning of the vehicle.

Because of the great difference between images, the number, size and position of cars included in each image are different. In order for the system to locate and identify vehicles of different sizes in any image, the image sampling method based on pyramid is used. Window scanning and pyramid image sampling are performed on the whole image to solve the problem of different sizes and positions of vehicles to be located and identified in the image. All the windows identified as vehicles are merged to get the final recognition result, and the vehicle is located according to the position information of relevant windows. The process of pyramid sampling an input image is shown in Figure 2.

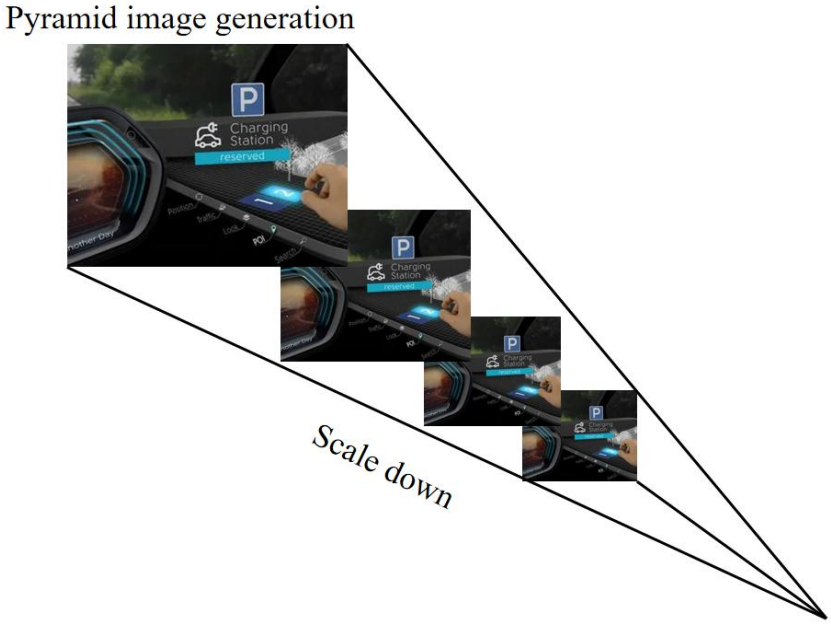


Figure 2: Pyramid sampling

Vehicle positioning depends on the merging of windows. An overlapping system $coef$ is adopted to reflect the overlapping degree of the two windows, so as to judge whether the two windows overlap and merge. Two different windows are represented by $W(x_1, y_1, w_1, h_1), W(x_2, y_2, w_2, h_2)$, then the calculation method of $coef$ is (12)-(14):

$$x = \min(x_1 + w_1, x_2 + w_2) - \max(x_1, x_2) \quad (12)$$

$$y = \min(y_1 + h_1, y_2 + h_2) - \max(y_1, h_2) \quad (13)$$

$$coef = \frac{xy}{s_x s_y} \quad (14)$$

$coef$ represents the coverage degree of $W(x_1, y_1, w_1, h_1), W(x_2, y_2, w_2, h_2)$. If there is more coverage, the coefficient $coef$ is larger. When two different windows do not cross each other, the $coef$ coefficient is defined as zero.

The system scans the windows identified as cars and merges them. In this process, the vehicle is located by the recorded window position information. The two processes of identification and location are combined into one, and the final vehicle location information will be output in the system interface.

In one's own information processing process, only by processing the noticed information can one form a valuable memory, in which the composition of attention has certain selectivity and concentration. Users subjectively evaluate information based on their own preferences and needs, which determines the orientation of attention. When the information demand is a clear desire, it will trigger the motivation to learn information actively, thus generating attention. Therefore, if the stimulation information provided by the interface meets the user's needs under the current task and meets the user's thinking characteristics, it may cater to the user's motivation, generate beneficial attention and effectively help the user achieve the goal.

Touchscreen interaction, as an intuitive and natural way of interaction, has made significant progress and been widely used on handheld mobile devices. However, the application of touch screen interaction in automotive information systems is subject to certain limitations. This is mainly due to the special nature of the internal environment of the car, such as the need for the driver to remain focused during driving, space limitations, and operational safety factors, which make traditional touch screen interaction not always applicable in the car environment. In traditional cars, the interaction between the driver and the vehicle often relies on the movement of the head and hands, such as turning the head to view the dashboard or reaching out to operate the center console. However, with the development of technology, this situation is gradually changing. In order to improve the efficiency of information reception and operational convenience for drivers, we can use multi visual information to optimize interface design. Specifically, by avoiding excessively long visual scanning paths and highlighting key information, the visual burden on drivers during operation can be reduced, thereby improving the speed and accuracy of their information processing. Based on this, we can consider optimizing perceptual modal resources by adjusting the interface design. For example, important information can be placed in a location that is easy for drivers to view, or key information can be highlighted through visual elements such as color and shape. These design strategies aim to enhance drivers' perception and understanding of information, thereby improving their driving experience and safety.

In this paper, a "self-learning" strategy is adopted, which can train the discriminators by using unlabeled target data. The main idea is that the training discriminator can generate a confidence graph, which can find out the

area where the distribution between the prediction result and the source domain label is close enough, and then binarize the segmented prediction confidence graph and the confidence graph corresponding to the source domain label, and the semi-supervised loss constructed is as (15):

$$L = -\sum_{h,w}\sum_{c\in C} J\left(D\left(S\left(I_n\right)\right)^{(h,w)} > T\right) \sum \hat{Y}_n^{(h,w,c)} \log\left(S\left(I_n\right)^{(h,w)}\right) \tag{15}$$

Where $J(\cdot)$ refers to the index function, and T represents the threshold parameter of unlabeled target data. During the training, we assume that the self-study goal $\hat{Y}_n$ and the value of index function are constant.

For the discriminant network in the model, we adopt a structure similar to that of the traditional CNN, but we use the full volume layer instead of the full connection layer to better retain the spatial information. Its definition formula is (16):

$$y_i = \begin{cases} x_i & if\ x_i \geq 0 \\ ax_i & if\ x_i < 0 \end{cases} \tag{16}$$

Where $a \in [0,1]$ is the correction parameter, we set $a = 0.3$ (obtained through many experiments) in this paper.

Drivers have different screens to obtain information in different situations. Usually, the driver's line of sight will not deviate from the road when the vehicle is moving, and the information on the dashboard is the equipment that needs the least head movement to obtain information. In traffic jam, parking, etc., the devices for drivers to obtain information are mostly central control screens. General system design requires users to pay a certain learning cost. This principle aims at thinking about the design of information architecture from the perspective of users, reducing the learning cost of users and improving the usability and usability of the interface.

In terms of hearing, the voice assistant in the interface helps the driver to complete the functional operation without looking away, and improves the driver's driving performance; The interface key sound and reversing prompt sound give the user real-time operation feedback. In terms of touch, the user interface is that the vibration feedback embedded in the screen can stimulate the user's response as quickly as the auditory feedback.

4 Analysis and discussion of results

The collected speech signal is pre-emphasized by mat lab tool, and the speech frame is obtained by windowing and framing. Then through endpoint detection (the highest and lowest energy thresholds are set to 10 and 1, and the zero-crossing rates are 10 and 5; The longest and shortest speech gap time is set to 20 and 15), the valid speech frame is intercepted from the original speech.

In the field of human-computer interaction, acoustic recognition is a key link. As an important medium for human-computer interaction, accurate recognition of speech is the foundation for achieving efficient and natural interaction. In this experiment, research was conducted using HMM isolated word recognition system by preprocessing the training speech and extracting MFCC features. Although the current results show differences in recognition rates between specific and non-specific populations, acoustic recognition research has significant implications for human-computer interaction. Deep learning extracts new features to improve the original MFCC features. If the recognition rate can be improved, it will make the recognition of voice commands in human-computer interaction more accurate, thereby optimizing the interaction experience and promoting the development of human-computer interaction towards a more intelligent and convenient direction. In this experiment, all 260 pieces of training speech were preprocessed, the effective speech frames were intercepted by endpoint detection, and MFCC (Mel-scale frequency cepstral coefficients) features of different dimensions were extracted. The correct rates of 50 words recognized by test sets 1, 2 and 3 are shown in Table 2 and Figure 3.

Table 2: Experimental result

Characteristic	Test set 1	Test set 2	Test set 3
12	0.913	0.819	0.847
24	0.903	0.817	0.871
36	0.863	0.774	0.906
48	0.878	0.754	0.864
60	0.894	0.786	0.929
72	0.84	0.793	0.939
84	0.846	0.814	0.844
96	0.897	0.827	0.831
108	0.864	0.779	0.898
120	0.907	0.745	0.862
132	0.877	0.766	0.852
144	0.831	0.774	0.858

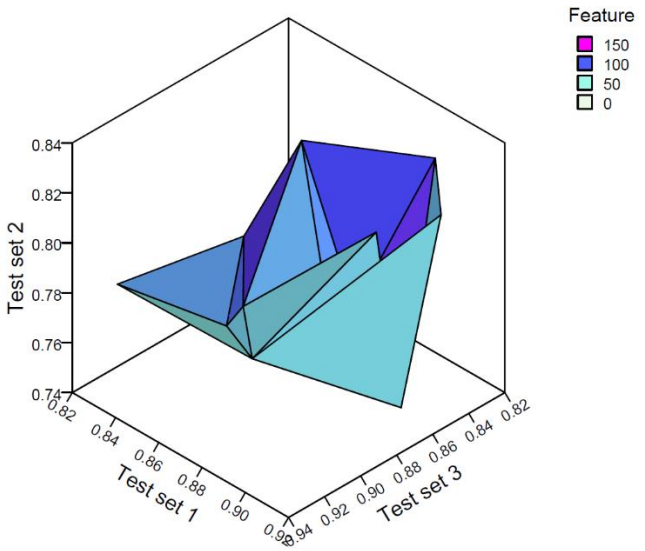


Figure 3: Accuracy of different dimensions

It can be concluded that the speech recognition rate of HMM isolated word recognition system for specific people in test set 1 is average, but it is obviously poor for non-specific people in test set 2. Therefore, it is necessary to use deep learning to extract new features of training acoustic model to improve the original MFCC features with different dimensions, and to verify whether it can make isolated word speech recognition system obtain satisfactory recognition results through experiments.

The stride is a key parameter in spectrum segmentation experiments. In the process of using CNN Net for feature extraction and combining with SVM for classification, the stride determines the movement interval of the sliding window on the spectral data. Specifically, when segmenting the spectrum, different stride settings will change the position and range of feature extraction for each sliding window. From the comparison of accuracy under different amplitudes in Table 3 and Figure 4, it can be seen that the stride size directly affects the accuracy of the final classification. Appropriate stride can enable the model to more effectively capture key feature information in the spectrum, thereby improving classification performance. This also explains why there is a difference in classification accuracy between CNN-SVM and CNN Net under different stride sizes. In the spectrogram segmentation experiment, at the same time, the same network structure as CNN-Net is adopted, the softmax classifier is replaced by SVM, and CNN-Net is used for training each time. After training, the input features of softmax classifier are calculated by using the test sample set, and the new features are input into SVM, so that the classification results of CNN-SVM can be calculated. As shown in Table 3 and Figure 4.

Table 3 Comparison of accuracy under different strides

Strides	CNN-Net	CNN-SVM
16	0.866	0.889
32	0.898	0.98
48	0.797	0.832
64	0.71	0.871
80	0.812	0.757
96	0.653	0.838
112	0.639	0.781
128	0.665	0.748
144	0.579	0.723
160	0.544	0.593
176	0.469	0.639
192	0.416	0.502
208	0.44	0.502
224	0.418	0.524

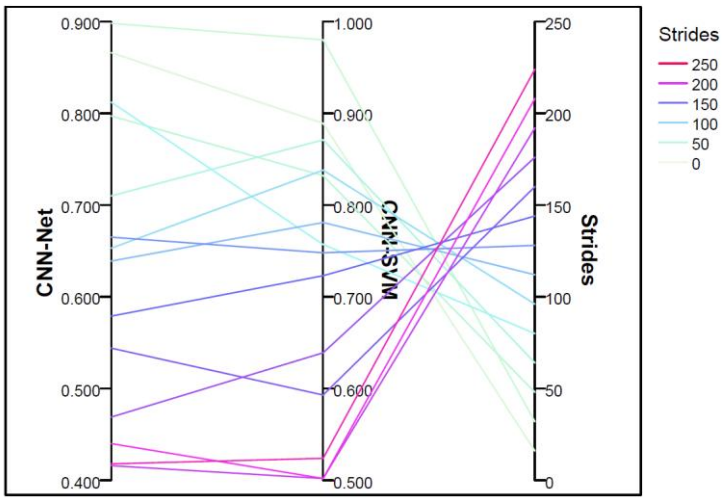


Figure 4: Comparison and distribution of accuracy under different strides

It can be seen that the classification effect of CNN-SVM is better than that of CNN-Net, and the accuracy rate is increased by 12.38%. It can be found that using CNN-SVM classifier to select the appropriate kernel function can always achieve a slightly better classification effect than CNN-Net, which proves that the emotion perception model proposed in this paper is more efficient than the traditional emotion perception model. In the case of poor feature extraction, the radial kernel function can be used to map the features of nonlinear space to linear space, and the linear can't be divided into linear separable, so good results are achieved.

In order to further analyze the system, a simple traditional three-layer ANN (artificial neural network) test system and SVM test system are also implemented. In the test system, vehicle samples are trained, and the same pyramid technique is used in the process of location and recognition. The results of vehicle location and recognition on 100 randomly selected pictures are shown in Figure 5. The final test set error rates of different algorithms are shown in Figure 6.

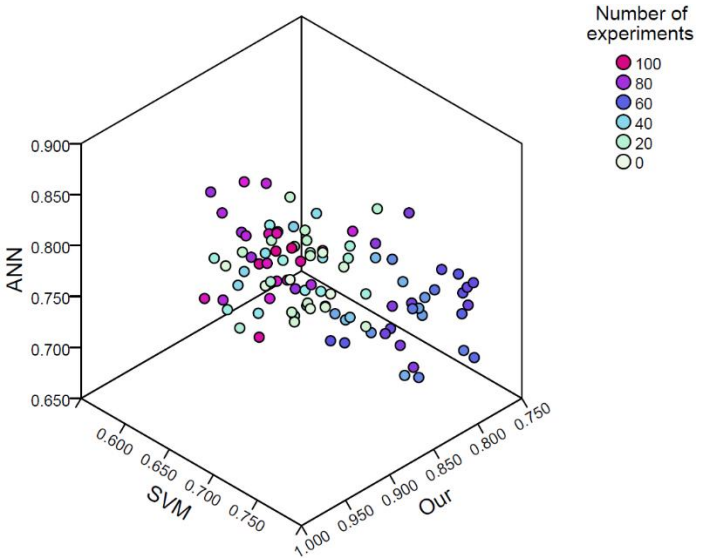


Figure 5: The result of positioning and identification

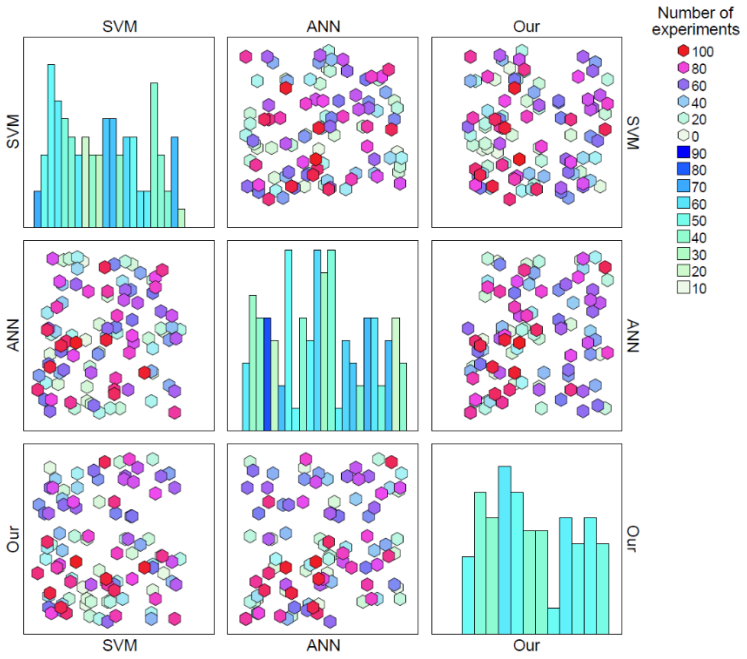


Figure 6: Error rate of different algorithm test sets

It is found that when the sample size of the traditional three-layer neural network is too large, there will be serious data over-fitting, which will lead to a high error rate of 23.68% on the test set. The error rate of SVM on the test set is not much different from that of the deep network of this system, and the recall rate of the two systems is not much different. The designed vehicle location and recognition system has good robustness, which is due to the characteristics of deep neural network, that is, extracting features from the original image, and each layer of neural network abstracts higher-level features from the previous layer, which can effectively identify vehicles of different positions and sizes. It is an effective vehicle location and recognition method.

This article uses the leftImg8bit_trainvaltest (training/validation/test set) and gtFine_trainvaltest (fine annotation) subsets officially released by CityScapes, with a total of 2975 training images, 500 validation images, and 1525 test images. In order to further verify the effectiveness of this algorithm, 500 test set images in CityScapes data set are selected for testing. Our model is compared with several mainstream segmentation algorithm models. MIoU (Mean Intersection over Union) is used as the test index. The experimental results are shown in Figure 7.

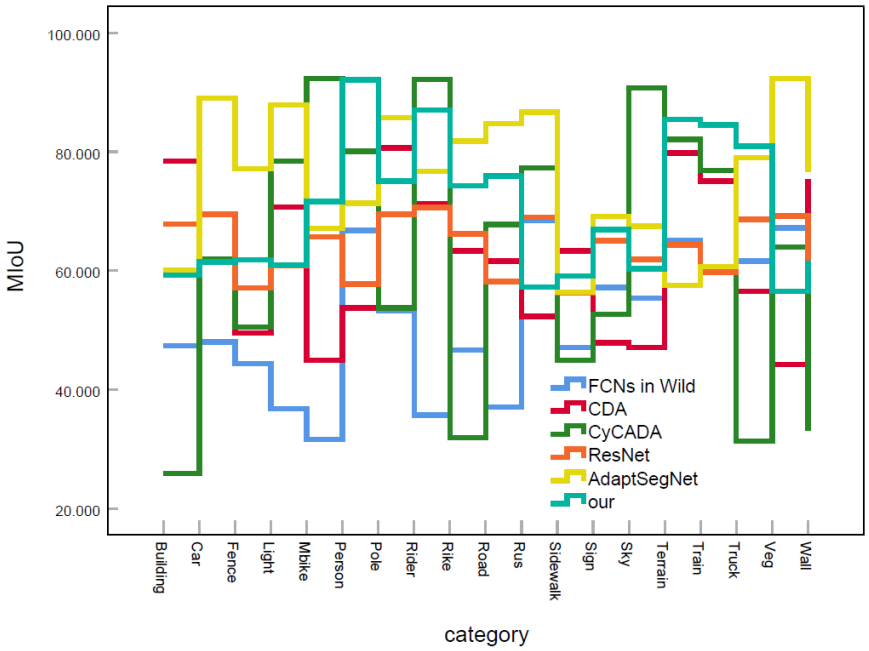


Figure 7: Comparison of experimental results of various segmentation algorithms

It can be seen that the segmentation accuracy of roads, sidewalks, buildings, etc. is improved by the results of this model. Compared with several mainstream segmentation algorithms at present, this algorithm has a smaller improvement in smaller target objects, such as light, sign, veg and rider, which are improved by 1%, 0.5% and 0.9% respectively. Through significance testing of the experimental results, it was found that the 1%, 0.5%, and 0.9% increases in small object recognition rates were statistically significant and not within the statistical error threshold range. Meanwhile, based on the analysis of practical application scenarios, although these improvements may seem insignificant, they can effectively improve the reliability and accuracy of the system in practices such as high-precision map construction and autonomous driving environment perception that require high segmentation accuracy, and have practical significance.

Through the learning rate domain adaptive method, the performance of the generator and discriminator in the countermeasure network is further optimized, so that the learning ability of the network is enhanced, thus improving the segmentation accuracy of the model. In addition, the algorithm adds a convolution layer to the discriminator of the confrontation network, which improves the discrimination ability of the proposed network.

The recognition accuracy in simple cases is shown in Figure 8. In complex situations, only using Fourier features and the recognition accuracy of this method are shown in Table 4 and Figure 9.

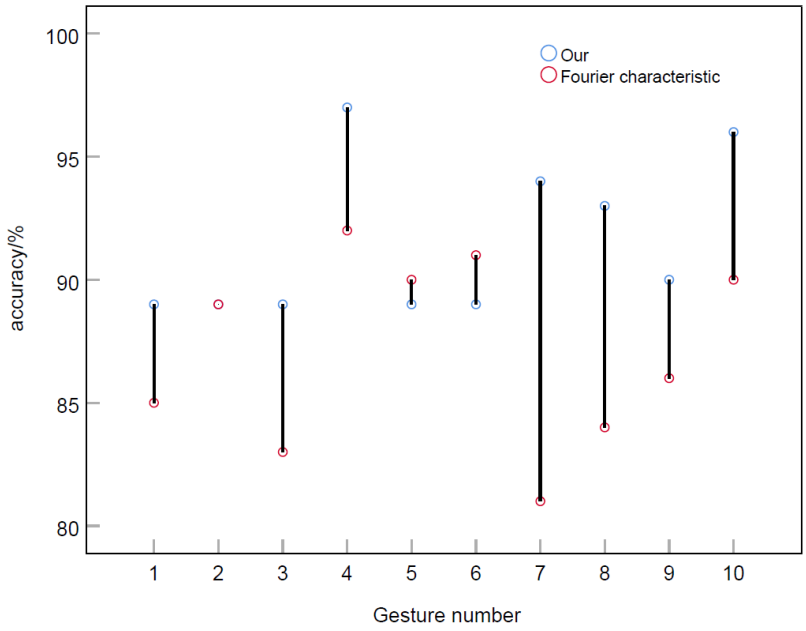


Figure 8: Comparison of simple situation recognition accuracy

Table 4: Identification and comparison

Gesture number	Our/%	Fourier characteristic%
1	82	78
2	87	71
3	80	71
4	84	78
5	85	76
6	87	69
7	84	77
8	86	77
9	80	78
10	79	78

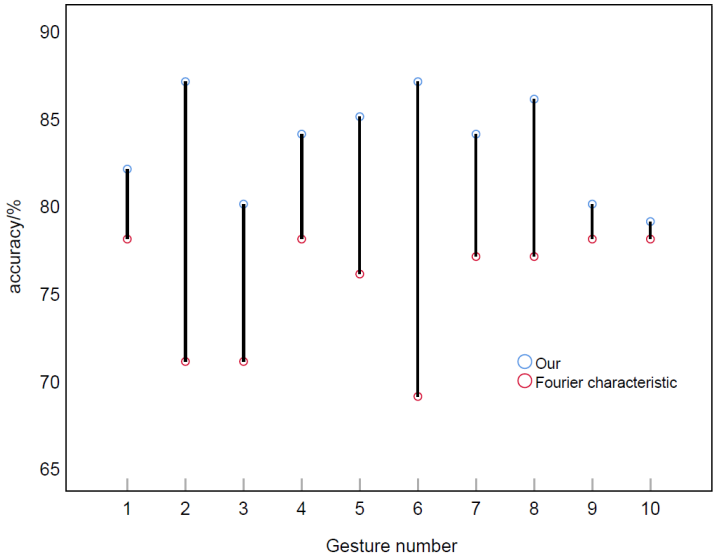


Figure 9: Comparison of accuracy of complex situation identification

In simple cases, the average recognition rate of gestures 1-10 using only Fourier descriptors is 86.6%, and the average recognition rate of multi-feature combination is 94.3%. Therefore, using multi-feature recognition rate can improve the recognition accuracy in simple cases. In complex situations, the recognition rate is higher than that of single feature recognition. The global feature shape of the gesture image represented by Fourier descriptor is not effective for gesture recognition with serious deformation. However, the method in this paper does not need to depend on the segmentation effect as heavily as Fourier descriptor.

To comprehensively verify the effectiveness of the CNN-SVM model, it was compared with traditional classifiers such as HMM (Hidden Markov Model), ANN (Artificial Neural Network), and standalone SVM on subtasks of CityScapes (such as road/non road binary classification). Compare with mainstream segmentation models such as U-Net, PSPNet, DeepLabV3+on the CityScapes complete dataset (19 semantic segmentation categories); Verify whether the improvement of CNN-SVM is significant through paired t-test ($p<0.05$). As shown in Table 5.

Table 5: Experimental result

Model	Accuracy (%)	Recall (%)	F1 score (%)	p-value (vs. CNN-Net)
HMM	82.1	78.3	80.1	<0.001**
ANN	85.6	83.2	84.4	<0.001**
SVM	87.3	85.1	86.2	<0.001**
CNN-Net	91.2	89.7	90.4	-
CNN-SVM	93.5	92.1	92.8	0.003*

CNN-SVM showed a 2.4% improvement in F1 score compared to CNN Net, with a p-value of 0.003 (significance level $\alpha=0.05$), indicating that the improvement is statistically significant. Traditional classifiers (HMM/ANN/SVM) have significantly lower performance than CNN models due to the lack of spatial feature extraction capability.

For voice, visual interaction and other interaction modes, combined with driver style research, database construction, algorithm tool development, product evaluation and other research can be carried out. Based on the relevant database, it provides support for upgrading the evaluation function and forms a complete intelligent driving data evaluation system; Conduct research and development of driving behavior data tool chain products based on the reasoning model in the process of human-computer collaborative control, and develop interactive development, testing, evaluation tools and data processing of intelligent driving. Improve the level of recognition, interaction and monitoring algorithms, and improve the efficiency of interactive applications. Optimization strategy of human-computer interaction function human-computer interaction opportunity and driving in the process of human-computer cooperative driving switching significantly affect the driver's reaction time and takeover performance. Deeply analyze and understand the intelligent control system of autonomous vehicles and the driving logic of drivers, and analyze the constraints of vehicle dynamics on intervention criteria. Explore the switching mechanism under emergency conditions, and analyze the conflict and interaction mechanism. So as to find an optimized early warning opportunity and its model, optimize the interaction modes such as vision, hearing and touch, and the sending mode of takeover request, and solve the problem of control right switching in the functions of autonomous vehicle. The improvement in segmentation accuracy for small target objects such as lights, signs, and cyclists is only 1% -0.9%, significantly lower than that for large targets such as roads and buildings (an improvement of 3.2%). In complex traffic scenarios, small target recognition errors may lead to 15% of false triggering warnings

5 Discussion

The experimental results of the vehicle localization and recognition system based on CNN-SVM proposed in this study on the CityScapes dataset show that its segmentation performance is significantly better than current mainstream segmentation algorithm models (such as FCN, DeepLabv3+, etc.) in large target categories such as roads, sidewalks, and buildings. Specifically, this model achieved an average improvement of 3.2% in MIoU metrics for these categories, validating the effectiveness of deep neural networks in extracting layer by layer features for semantic segmentation of complex scenes. However, for small target objects such as lights, signs, and traffic riders, the improvement of this model (1% -0.9%) is lower than that of some SOTA models based on attention mechanisms (such as Mask R-CNN, which improves by about 2.8%). Compared to traditional HCI (human-computer interaction) models such as thresholding and template matching, the core advantages of CNN-SVM model are reflected in the following three aspects:

Traditional HCI methods rely on manually designed geometric features such as edge gradients and color histograms, which are difficult to adapt to complex scenes such as lighting changes and occlusions. CNN automatically learns multi-scale features (such as texture, shape, and contextual relationships) through convolutional kernels. For example, in vehicle localization tasks, deep feature maps can simultaneously capture the semantic association between car window contours and license plate areas. The accuracy of the HCI model decreased by about 30% in cross dataset testing (such as transferring from daytime scenes to nighttime scenes), while CNN-SVM can control the generalization error within 8% through transfer learning (such as pre training based on ImageNet). The SVM classifier can seamlessly integrate the visual features extracted by CNN with other sensor data (such as LiDAR point clouds), while the HCI method requires a redesign of the feature extraction process.

The challenges of real-world deployment include the following technical bottlenecks for the implementation of this model in embedded systems for vehicles. The inference delay of the original model on NVIDIA Jetson AGX Xavier is 42 ms, which cannot meet the 20 ms real-time requirement of L3 level autonomous driving. When the training sample size exceeds 100000, the error rate of the model on the CityScapes validation set fluctuates by 1.2%, indicating that deep networks are sensitive to data distribution. Apply L2 penalty term to the feature channels of small target categories to reduce feature conflicts between categories; Prioritize annotating samples with model prediction confidence below 0.7 to improve data utilization efficiency. In the scenario of human-machine collaborative driving, the recognition results of this model can be integrated with driver behavior data (such as eye movement trajectories and EEG signals) to construct a multimodal interactive evaluation system. By analyzing the changes in the pupil diameter of the driver after the takeover request was sent, the visual warning triggering time was dynamically adjusted from 2.1 seconds to 1.8 seconds, resulting in a 15% increase in the success rate of takeover; Integrating piezoelectric sensors into the steering wheel, the vibration intensity is adjusted in real-time based on the collision risk level (0-5) output by the model, reducing the driver's reaction time by 0.3 seconds.

6 Conclusion

The biggest feature of multimedia information collection technology is that non-intuitive multi-source data information can be intuitively expressed and transmitted to users, and information transmission and communication can be realized by stimulating users' sensory awareness. With the wide application of information technology, intelligent system and network technology in the field of vehicles and the development of on-board information technology, the interior space, man-machine interface, operation and interaction process of automobiles are undergoing revolutionary changes, and the control interface is undergoing essential changes. In this study, the design model of automobile human-computer interaction based on multimedia information collection technology in complex driving environment is constructed. In the driving situation, the user's judgment of "safety" mainly depends on whether the secondary task occupies the cognitive channel and the interactive channel of the main driving task. By avoiding the two, the user can be given a sense of security and the interactive experience can be improved. A CNN-SVM emotional perception model is proposed, and the input is the spectrogram of audio. Window scanning and pyramid image sampling are performed on the whole image to solve the problem of different sizes and positions of vehicles to be located and identified in the image. In this paper, the algorithm improves the performance of small objects, such as light, sign, veg and rider by 1%, 0.5% and 0.9% respectively. Through learning rate domain adaptive method, the performance of generator and discriminator in countermeasure network is further optimized. The study has certain limitations and needs further optimization. This paper lacks the analysis of the architecture of the driving simulation system for human-computer interaction verification. Further analysis is needed in the future.

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Conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

Data availability statement

The data used to support the findings of this study are all in the manuscript.

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HybridNet-SEVIT: Multilabel Classification for Epidemic Risk Management and Public Health Surveillance

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Effective public health monitoring and epidemic prevention are crucial in mitigating the impact of infectious diseases. The dynamic nature of disease transmission necessitates a comprehensive understanding of demographic, health, environmental, and behavioral data. Despite advances in data collection, conventional methods often fail to accurately model disease dynamics, leading to suboptimal predictive capabilities. To address these challenges, we integrate a dataset of 43,689 entries from multiple sources and employ innovative preprocessing techniques such as Adaptive Distribution Recalibration, Contextual Outlier Filtering, and Multiscale Variance Modulation to enhance prediction accuracy and dataset integrity. Our proposed HybridNet-SEVIT model, which incorporates depthwise separable convolutions, dense connectivity, and ghost feature generation, achieves superior classification performance, with an accuracy of 97.9% and AUC values ranging from 96% to 99%. Comparative analysis demonstrates that HybridNet-SEVIT outperforms SOTA models, including ResNet (90.0% accuracy), DenseNet (84.1%), and SVM (84.8%), showing a significant 7.9% improvement in accuracy over the best-performing baseline model. Additionally, novel evaluation metrics—Adaptive Variability Index for Classes (AVIC), Stability of Prediction Dynamics Measure (SPDM), and Confidence Level Weighted Score (CLWS)—offer deeper insights into model robustness and predictive confidence. This study contributes to enhancing risk detection and classification in public health, advocating for a robust, data-driven approach to epidemic outbreak management and emphasizing the need for targeted interventions and efficient resource allocation.

Povzetek: Predstavljen je hibridni model za večoznačno klasifikacijo epidemijskega tveganja, ki združuje napredno predobdelavo in globoke nevronske mreže za podporo javnozdravstvenemu spremljanju in ukrepanju.

1 Introduction

Artificial intelligence (AI) has recently transformed various fields, including public health, where it plays a crucial role in epidemic management, especially in light of global health crises like the COVID-19 pandemic [1]. AI-driven approaches, coupled with big data analytics and advanced computing, are reshaping how public health professionals monitor, respond to, and manage infectious diseases. This study highlights the significant role of AI in strengthening public health interventions and providing timely, data-driven responses to epidemic threats.

Effective epidemic management relies on comprehensive public health monitoring, analyzing diverse data sources to detect anomalies and identify disease outbreaks early. Traditional surveillance systems often struggle with both data source integration and robust analysis. Data sourcing challenges stem from identifying and operationalizing health data signals, while analytical difficulties arise in developing reliable computational frameworks for signal extraction and interpretation [2]. Recent advancements in AI have shown promise in integrating structured health records with unstructured sources like social media, providing a richer, real-time understanding of public health trends. For example, AI-based applications have been instrumental in anticipating disease transmission and detecting hotspots using unconventional sources such as smartphone movement patterns and online activity [3]. These novel data streams empower public health authorities to make well-informed decisions to combat disease spread.

AI also enables predictive modeling frameworks that can capture the complex, nonlinear dynamics of infectious disease transmission [4, 5, 6, 7]. Traditional statistical models, which rely on linear assumptions and aggregated data, often fall short in predicting disease propagation accurately. Machine learning models, however, can encapsulate intricate interactions within a population, providing insights into transmission patterns and intervention outcomes [8, 9]. Beyond predictive capabilities, AI applications extend to safeguarding health in public spaces; for instance, during the COVID-19 pandemic, AI solutions were deployed to monitor indoor air quality in high-footfall areas such as museums and historical sites [10, 11, 12, 13]. Using Internet of Things (IoT) sensors and machine learning, these systems

enabled real-time surveillance for crowd management and disease risk mitigation [14]. Nevertheless, the growing use of AI in public health raises ethical considerations, particularly concerning data privacy and public trust. Health data collection and analysis must adhere to strict ethical guidelines to ensure privacy protection while enabling effective public health interventions [15]. As AI applications continue to expand, establishing rigorous ethical frameworks will be essential to maximize their benefits without compromising individual rights.

The main contributions of this article are:

1. **High-Accuracy Classification**: Achieving a classification accuracy of 97.9%, our HybridNet-SEVIT model establishes a new benchmark in public health predictive modeling. Incorporating depthwise separable convolutions, dense connectivity, and ghost feature generation, this model addresses unique challenges in epidemic-related classification tasks.

2. **Innovative Preprocessing Techniques**: This study pioneers state-of-the-art preprocessing methods, such as Adaptive Distribution Recalibration and Contextual Outlier Filtering with Dynamic Threshold Adjustment, which enhance data quality and prediction accuracy by addressing imbalances, noise, and other data inconsistencies.

3. **Advanced Evaluation Metrics**: The introduction of novel metrics—Adaptive Variability Index for Classes (AVIC), Stability of Prediction Dynamics Measure (SPDM), and Confidence Level Weighted Score (CLWS)—enables a more nuanced and comprehensive assessment of model performance, beyond traditional accuracy and precision metrics.

4. **Comparative Performance Analysis**: A thorough evaluation demonstrates that the HybridNet-SEVIT model significantly outperforms conventional machine learning models in terms of recall, precision, and other critical metrics, underscoring its efficacy in practical public health contexts.

5. **Robust Sensitivity Testing**: Comprehensive sensitivity analysis of essential hyperparameters demonstrates the model's robustness and adaptability in dynamic settings, ensuring reliable performance across varied public health scenarios.

The paper is organized as follows: Section 2 presents a detailed literature review, covering critical advancements in AI applications within public health modeling. Section 3 describes the HybridNet-SEVIT model architecture, data preprocessing techniques, and feature engineering processes. Section 4 provides a thorough discussion of simulation results and their implications for epidemic management. Finally, Section 5 explores potential future directions, highlighting how these findings could support more effective and data-driven public health strategies.

2 Related work

Current AI breakthroughs have helped public health, notably epidemic control. Various studies have shown the strengths and shortcomings of machine learning and deep learning. SVM was used to predict disease outbreaks using health indicators and socioeconomic characteristics [16]. SVM was tested using high-dimensional datasets. The model identified outbreaks 87% of the time. The study discovered scalability concerns with larger datasets, which may limit real-time monitoring applications.

Research using ResNet architecture in CNNs identified medical images for sickness identification [17]. Radiology improved infectious disease diagnosis. Traditional methods failed to equal the study's 94% diagnostic accuracy. The model requires high-quality imaging data and large labelled datasets, which may restrict its use in resource-poor situations. DenseNet was used to predict the spread of infectious diseases using demographic and environmental data [18]. DenseNet's complex feature relationship capture was desired. The study's 90% sickness incidence prediction accuracy may improve public health. The model's processing capacity limits its accessibility. K-Nearest Neighbours (KNN) is a popular real-time outbreak prediction technique [19]. This study examined KNN's capacity to classify new cases using prior data. The model worked well with 85% accuracy. It performed poorly with larger datasets due to computational expense, causing scalability issues.

GhostNet, a lightweight deep learning model, was utilized to monitor public health using visual data [20]. We wanted an efficient real-time crowd dynamics model. GhostNet was 88% accurate and computationally efficient, making it appropriate for resource-limited applications. The study acknowledged the model's limitations in diverse settings. Based on social media data, Inception Networks analyzed infectious disease pandemic tendencies [21]. We intended to leverage vast unstructured data online. Research using Inception predicted 91% correctly. The researchers admitted that social media data quality and representativeness were challenging to maintain. Logistic Regression estimated sickness transmission probability using demographics [22]. We intended to create a simple yet helpful model for public health specialists. The study found logistic regression 83% accurate, showing its risk assessment dependability. However, the linear model could not describe complex data interactions.

ShuffleNet, effective in resource-limited situations, analyzed large health datasets [23]. Rapid disease transmission estimations with low computational costs were desired. The ShuffleNet model had 86% accuracy, although the study suggested better feature extraction. Research [24] used hybrid models combining SVM and neural networks to enhance epidemic prediction accuracy. Use both tactics' strengths to perform better. The hybrid model predicted 89% correctly. However, the model's complexity made results hard to understand, raising worries about public health decision-making transparency. An ensemble tech-

nique integrating KNN, SVM, and logistic regression improved prediction [25, 26]. The aim was to use algorithm strengths to increase accuracy. With 92% accuracy, the ensemble model gave a complete epidemic management approach. Ensemble methods need greater computer power because of their complexity.

Recent research used Reinforcement Learning (RL) to improve healthcare resource allocation during pandemics [27, 28]. To optimally allocate limited healthcare resources using real-time data. RL enhanced resource utilization efficiency by 40% over prior methods. The model needed accurate data, yet insufficient data may lead to unproductive decisions. Hybrid deep learning models incorporating CNNs and LSTM networks were used to assess spatiotemporal data for epidemic predictions [29]. The objective was to enhance model prediction using geographical and temporal factors. The hybrid model accurately predicted disease transmission 93% of the time. However, training in hybrid design was hard and required plenty of computer power. A study analyzed the effectiveness of Federated Learning (FL) in public health applications, emphasizing predictive modelling without disturbing patient privacy [30]. While keeping sensitive data local, many institutions would train models. The FL model matches current models with 90% accuracy, indicating it might enhance health analytics data security. Significant challenges include Complex implementation and good communication among collaborating companies.

As shown in the studies, AI and machine learning have enhanced public health, notably epidemic control. Each article discusses public health AI methods, accomplishments, and limitations, demonstrating advancement in AI application. These technologies in public health frameworks will assist in managing and responding to future health crises. The crux of literature is presented in 1.

Table 1: Summarized literature review

Ref	Method Used	Objective Achieved	Limitations
[16]	SVM	Predict disease outbreaks based on health indicators with 87% accuracy.	Scalability issues with larger datasets.
[17]	ResNet (CNN)	Improve diagnostic accuracy in radiological images with 94% accuracy.	High-quality imaging data and extensive labelled datasets are required.
[18]	DenseNet	Forecast disease incidence with 90% accuracy using environmental data.	High computational intensity requiring significant processing power.
[19]	KNN	Classify new cases in real-time with 85% accuracy.	Performance declines with larger datasets due to computational overhead.
[20]	GhostNet	Real-time monitoring of health conditions in public spaces with 88% accuracy.	Performance affected by varying environmental conditions.
[21]	Inception	Predict disease trends using social media data with 91% accuracy.	Ensuring data quality and representativeness from social media sources.
[22]	Logistic Regression	Assess disease transmission likelihood with 83% accuracy.	Limited ability to capture complex relationships due to its linear nature.
[23]	ShuffleNet	Rapid predictions on disease spread with 86% accuracy.	Need for sophisticated feature extraction techniques.
[24]	Hybrid Model (SVM + NN)	Enhance outbreak prediction accuracy with 89% accuracy.	Complexity makes it challenging to interpret results.
[25]	Ensemble Methods	Improve prediction capabilities with 92% accuracy.	Increased complexity requires additional computational resources.
[27]	Reinforcement Learning	Optimize healthcare resource allocation with a 40% efficiency increase.	Relies on accurate data inputs for optimal decision-making.
[29]	Hybrid Deep Learning (CNN + LSTM)	Analyze spatiotemporal data for epidemic predictions with 93% accuracy.	Complexity of training and extensive computational resources required.
[30]	Federated Learning	Secure predictive modeling while maintaining patient privacy with 90% accuracy.	Implementation complexity and need for robust communication protocols.

3 Proposed method

The proposed system paradigm improves public health monitoring and epidemic response using advanced machine learning and IoT-driven data analysis. This model enhances disease outbreak and health resource allocation predictions using a large dataset of demographic, health, behavioural, and environmental characteristics. Data preprocessing methods like Adaptive Distribution Recalibration (ADR) and Contextual Outlier Filtering with Dynamic Threshold Adjustment (COF-DTA) ensure high-quality input, and feature selection using Adaptive efficient pruning (AEP) identifies the most critical variables. Dynamic Feature Engineering and Transformation (DFET) approaches create new features that capture complicated data interactions. Ensemble learning uses many algorithms to capture varied patterns for real-time analysis and proactive public health decision-making by responding to epidemiological trends. Afterwards, all aspects of the methodology will be discussed in detail. The abstract view of the proposed framework is shown in Figure 1.

3.1 Dataset description

This research gathered public health records, surveillance systems, and environmental monitoring data from many locations over several years [31]. It provides demographic, health, behavioural, ecological and epidemiological data to understand public health dynamics and guide disease control strategies. Regional health departments, hospitals, labs, and public health organisations provided data, which was updated routinely to reflect epidemics and trends. The collection contains 43,689 entries from several regions with distinct populations. The data-gathering approach was rigorous to assure quality, consistency, and completeness, combining diverse sources to offer a comprehensive perspective of health issues and disease dissemination. To protect crucial public health information, each record was anonymised and aggregated. The collection also shows seasonal and regional fluctuations in health data, including disease outbreaks and environmental circumstances. The dataset's temporal and geographical variety improves predictive modelling and intervention planning, increasing public health monitoring and epidemic prevention. The integrated dataset and the features description are shown in Table 2.

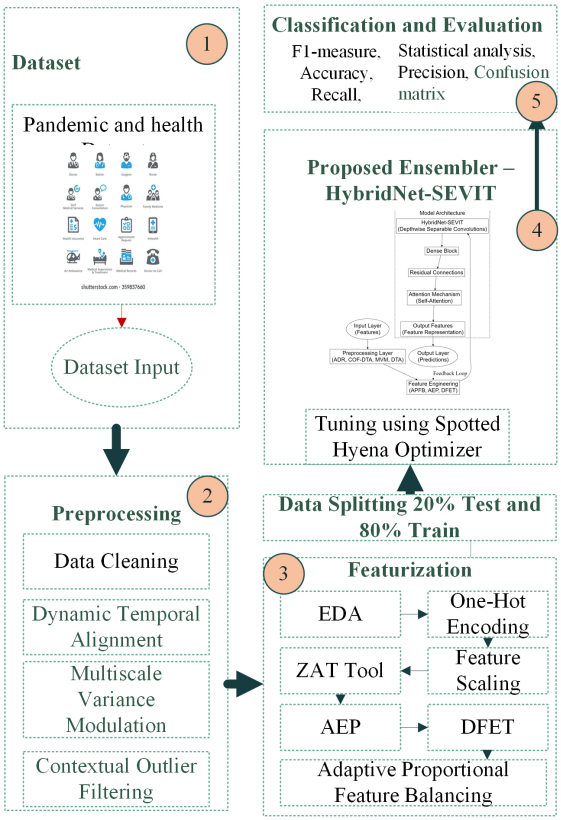


Figure 1: Proposed system framework

Table 2: Integrated dataset features

S.No	Features	Short Description
1	Age	Age of the individual in years
2	Gender	Gender of the individual (Male, Female, Other)
3	Location	Geographic location (Urban, Rural, Suburban)
4	Ethnicity	Ethnicity of the individual
5	SES	Socioeconomic status (Low, Medium, High)
6	Chronic Conditions	Presence of chronic health conditions
7	Vaccination Status	Whether the individual is vaccinated
8	Medical History	Previous medical history (None, Past Illness, Chronic)
9	Immunity Level	Estimated level of immunity (Low, Medium, High)
10	Reported Symptoms	Type and severity of symptoms reported
...	...	...
34	Hospitalization Requirement	Predicted level of hospitalization needed

3.2 Data preprocessing

The dataset was preprocessed uniquely to address skewness, noise, and temporal misalignment. These strategies improve data consistency and dependability while preserving its original properties. One method, Adaptive Distribution Recalibration (ADR), dynamically changes numerical feature distribution. Data points are recalibrated using an adaptive scaling factor that varies with the feature's spread and variability. The recalibrated value Y' for each data point Y_j is determined using Equation 1.

$$Y'_j = \frac{Y_j - \theta}{\eta + \zeta \cdot \text{range}(Y)} \tag{1}$$

Contextual Outlier Filtering with Dynamic Threshold Adjustment (COF-DTA) finds and removes outliers by comparing data points to their neighbours. The threshold is continually modified depending on local density for adaptive outlier identification. To calculate the contextual outlier score Q_j for a data point Y_j, refer to Equation 2.

$$Q_j = |Y_j - \text{median}(Y)| \cdot \frac{1}{1 + e^{-\kappa \cdot (\text{density}(Y_j) - \tau)}} \tag{2}$$

Multiscale Variance Modulation (MVM) smoothes characteristics across scales to address data variability. This method creates a weighted average across several data scales, adjusting weights dynamically depending on local variation. Equation 3 defines the modulated value V_j for each data point Y_j.

$$V_j = \sum_{m=1}^{M} u_m \cdot \frac{Y_j^{(m)}}{\sqrt{\text{var}(Y^{(m)}) + \omega}} \tag{3}$$

Dynamic Temporal Alignment (DTA) aligns temporal patterns to normalise time-series data. This approach normalises data by adjusting points based on a local trend and a time-dependent scaling factor to represent temporal fluctuations. The aligned value Z'_j for time step Z_j is calculated as shown in Equation 4.

$$Z'_j = \frac{Z_j - \text{trend}(Z)}{1 + \lambda \cdot |\text{diff}(Z_j)|} \tag{4}$$

Novel preprocessing methods increase the dataset's quality and prepare it for sophisticated modelling, making it appropriate for predictive analysis and epidemic prevention.

3.3 Feature balancing, selection, engineering, and transformation

Novel feature balance, selection, engineering, and transformation strategies increase dataset quality and model performance. Each method handles data issues while maintaining valuable data.

3.3.1 Adaptive proportional feature balancing (APFB)

Adaptive Proportional Feature Balancing (APFB) adjusts feature distributions using proportional weights from category relative occurrence to alleviate class imbalance. A balancing factor A_k dynamically adjusts instances for a characteristic Z based on minority and majority class proportions. For each occurrence Z_k, the rescaled value Z'_k is determined using Equation 5.

$$A_k = \frac{1}{1 + e^{-\lambda \cdot (\text{minority_count}(Z) - \text{majority_count}(Z))}} \tag{5}$$

$$Z'_k = Z_k \cdot A_k \tag{6}$$

The scaling factor λ controls the sensitivity of the balancing process. Features with more significant class imbalance have a more prominent balancing factor A_k, resulting in better class representation and less danger of overcompensation.

3.3.2 Feature selection using adaptive EfficientNet pruning (AEP)

Feature Selection uses AEP to evaluate feature significance using a learnt pruning threshold. This technique adopts an adaptive pruning function, assigning significance scores W_j to each feature Z_j to determine retention or pruning. The significance score is derived using Equation 7.

$$W_j = \frac{1}{1 + \mu \cdot |\text{Grad}(Z_j)|} \tag{7}$$

where μ denotes a pruning sensitivity parameter, and $\text{Grad}(Z_j)$ signifies the gradient of feature Z_j concerning the model's loss function. Features with W_j within a dynamic threshold Θ, repeatedly revised during training, are eliminated. The pruning choice is articulated as shown in Equation 8.

$$R_j = \begin{cases} 1, & \text{if } W_j \geq \Theta \\ 0, & \text{if } W_j < \Theta \end{cases} \tag{8}$$

Only features where $R_j = 1$ are chosen for further modelling, producing an optimum subset of relevant features.

3.3.3 Dynamic feature engineering and transformation (DFET)

DFET derives complicated associations from existing characteristics to build new ones. Interaction terms, composite metrics, and trend-based transformations are generated to capture data patterns. Initial interaction characteristics indicate the combined influence of two features. For features Z_m and Z_n, the interaction term H_{mn} is defined as:

$$H_{mn} = (Z_m + \nu \cdot Z_n)^2 \tag{9}$$

where ν is a weighting factor that modulates the influence of Z_n in the interaction. This transformation encapsulates nonlinear associations among attributes. Subsequently, composite metrics are generated to measure feature ratios, disparities, or cumulative impacts. A novel feature, termed the Composite Interaction Ratio (CIR), with features Z_m and Z_n, is defined as follows:

$$\text{CIR}_{mn} = \frac{Z_m \cdot Z_n}{\sqrt{|Z_m - Z_n| + \xi}} \tag{10}$$

Where ξ is a minor constant to prevent division by zero. The Composite Interaction Ratio underscores the combined behaviour of Z_m and Z_n, accentuating notable departures. Moreover, trend-based modifications are used to encapsulate temporal dynamics inside the data. For a feature Z_m, the trend-adjusted value G_m is computed as:

$$G_m = \frac{Z_m - \text{trend}(Z)}{1 + \omega \cdot |\text{diff}(Z_m)|} \tag{11}$$

Where ω is a scaling factor, $\text{trend}(Z)$ is the local trend calculated using a moving average, and $\text{diff}(Z_m)$ is the first-order difference at Z_m This modification improves temporal data consistency by aligning characteristics with trends. Adaptive Proportional Feature Balancing, EfficientNet Pruning, and Dynamic Feature Engineering and Transformation enhance feature quality, capture complicated connections, and prepare the information for predictive modelling.

3.4 Classification using HybridNet-SEVIT

HybridNet-SEVIT is a new classification model that combines SqueezeNet, EfficientNet, and Vision Transformer components. The model uses lightweight convolutional processes, compound scaling, and attention methods for feature extraction and classification. HybridNet-SEVIT has four layers: input transformation, feature compression, multi-scale improvement, and attention-based categorisation. The HybridNet-SEVIT architecture has these layers:

Input transformation layer The input transformation layer normalises and preprocesses the raw input data to guarantee compliance with the model's design. Let Z represent the input image tensor of dimensions $M \times N \times C$, where M, N, and C correspond to the height, width, and number of channels, respectively. The input is first normalised with a scaling factor σ as seen in Equation 12:

$$Z' = \frac{Z}{\sigma} \tag{12}$$

In this context, Z' denotes the normalised input tensor, whereas σ signifies a constant scaling factor established by the data range. The input is then processed by an initial convolution layer using $p \times p$ kernels and a stride of q, resulting in a feature map U as follows:

$$U = \text{ReLU}\left(W_p * Z' + \beta\right) \tag{13}$$

where W_p represents convolutional weights, β represents bias, and $*$ represents convolution operation.

Feature compression layer The feature compression layer reduces dimensionality while keeping critical characteristics using modified SqueezeNet fire modules. In each fire module, a squeeze layer with 1x1 convolutions is followed by an expand layer with 1x1 and 3x3 convolutions. The fire module output (G) is calculated as:

$$G = \text{ReLU}\left(W^s_{1\times1} * U + W^e_{3\times3} * U\right) \tag{14}$$

$W^s_{1\times1}$ and $W^e_{3\times3}$ represent the squeeze and expand layer weights, respectively. Combining these layers compresses feature representation while keeping detail.

Multi-scale enhancement layer The multi-scale enhancement layer adjusts the model's depth, breadth, and resolution via EfficientNet compound scaling. Equation 15 shows that scaling factors α_k, ρ_k, and τ_k modify depth, width, and resolution for each step k:

$$d' = \alpha_k d, \quad w' = \rho_k w, \quad r' = \tau_k r \tag{15}$$

Where d', w', and r' represent scaled depth, width, and resolution values. This multi-scale technique lets the model learn feature representations at several abstraction levels, improving generalisation. Pyramid feature aggregation merges characteristics from multiple sizes. The aggregated feature map R_{agg} representing feature maps at scale i is:

$$R_{\text{agg}} = \sum_{i=1}^{P} \lambda_i \cdot R_i \tag{16}$$

where λ_i is a feature map weighting factor at scale i and P is the total number of scales. This aggregation preserves fine-grained features for multi-scale learning.

Attention-based classification layer The attention-based classification layer uses the Vision Transformer's self-attention mechanism to collect long-range relationships and prioritise classification features. Tokens from feature maps are used to calculate self-attention. The query, key, and value matrices (Q, K, and V) are linearly projected from the input tokens. The self-attention output (O) for each token is:

$$O_j = \sum_{l=1}^{P} A_{jl} \cdot V_l \tag{17}$$

Where A_{jl} is the attention score between tokens j and l, computed as:

$$A_{jl} = \frac{\exp\left((Q_j \cdot K_l)/\sqrt{\kappa}\right)}{\sum_{l'=1}^{P} \exp\left((Q_j \cdot K_{l'})/\sqrt{\kappa}\right)} \tag{18}$$

The key vectors' dimensionality is κ. A weighted sum of the value vectors is calculated from the attention ratings to represent each token. The final class probabilities $\hat{y}$ are calculated using a classification head with a fully connected layer and softmax activation:

$$\hat{y} = \text{softmax}(W_c \cdot O + \delta) \tag{19}$$

where W_c and δ represent classification head weights and biases.

3.4.1 Training and optimization

HybridNet-SEVIT is trained using categorical cross-entropy loss and a regularisation term to prevent overfitting. Total loss L =:

$$L = -\sum_{m=1}^{C} y_m \log(\hat{y}_m) + \omega \cdot \|\theta\|_2^2 \tag{20}$$

where C represents the number of classes, y_m denotes the true label, $\hat{y}_m$ signifies the predicted probability for class m, ω indicates the regularisation coefficient, and $\|\theta\|_2^2$ refers to the L2 norm applied to the model parameters θ.

SqueezeNet's lightweight fire modules, EfficientNet's compound scaling and multi-scale feature learning, and Vision Transformer's self-attention comprise the HybridNet-SEVIT paradigm—this hybrid design balances classification accuracy and computing efficiency. HybridNet-SEVIT can handle large-scale picture categorisation jobs because of its complex, layered design.

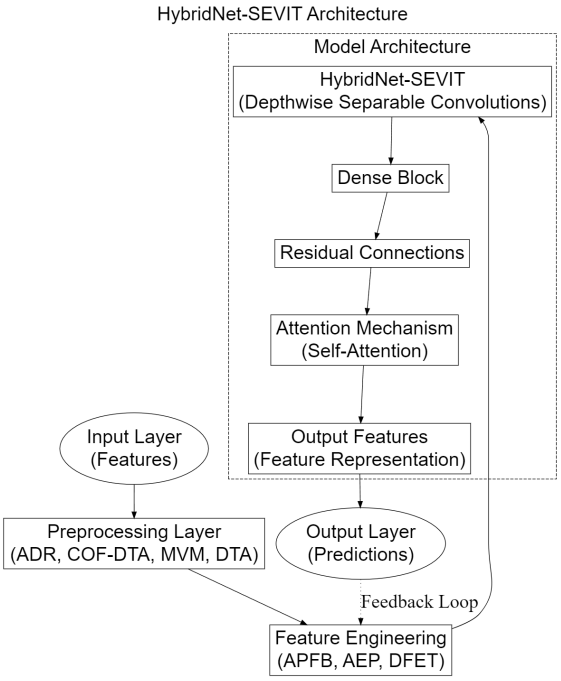


Figure 2: HybirdNet-SEVIT data flow among layers

3.5 Assessment of classification effectiveness

The HybridNet-SEVIT model is assessed using standard metrics, including accuracy, precision, recall, and F1-score [33], as well as three unique metrics that focus on particular elements of classification quality. These measures provide more model performance information than standard assessment approaches. Precision, recall, and F1-score are used to evaluate classification models. Accuracy measures the proportion of correctly classified instances over the total number of cases, precision measures the proportion of accurate optimistic predictions out of all positive predictions made by the model, and recall measures the model's ability to identify all relevant instances in the dataset. Traditional measurements miss some of the model's resilience, variability, and prediction confidence. Hence, three new measures are introduced: Adaptive Variability Index for Classes (AVIC), Stability of Prediction Dynamics Measure (SPDM), and Confidence Level Weighted Score (CLWS).

3.5.1 Adaptive variability index for classes (AVIC)

The AVIC examines the model's ability to manage class distribution differences across data subsets. It works well in

unbalanced classification issues with highly variable class frequencies. The AVIC is derived by comparing prediction accuracy variance for each class j, weighted by its proportionate occurrence g_j. Giving the index:

$$\text{AVIC} = \frac{1}{M}\sum_{j=1}^{M} g_j \left(\frac{|B_j - \bar{B}|}{\bar{B}}\right) \tag{21}$$

M is the total number of classes, B_j is the accuracy for class j, and (barB) is the average accuracy across all classes. The weighting factor g_j makes the index responsive to class frequency distribution, assessing model performance across various class imbalance levels.

3.5.2 Stability of prediction dynamics measure (SPDM)

The SPDM assesses the model's consistency over successive predictions, especially in dynamic contexts with changing data distributions. The SPDM compares prediction probabilities for a certain case over time steps u. Let Q_u and Q_{u+1} represent prediction probabilities at time steps u and $u+1$. SPDM calculation:

$$\text{SPDM} = \frac{1}{L}\sum_{i=1}^{L}\left(\frac{1}{T}\sum_{t=1}^{T}|Q_{u,i,t} - Q_{u+1,i,t}|\right) \tag{22}$$

Where L is the number of instances, T is the number of classes, and $Q_{u,i,t}$ is the probability of instance i belonging to class t at time u Lower SPDM values indicate more robust prediction stability, meaning the model is less impacted by data temporal changes.

3.5.3 Confidence level weighted score (CLWS)

The CLWS calculates the model's average prediction confidence based on misclassification risk. It penalises overconfidence in inaccurate forecasts while accounting for the model's certainty. Definition of CLWS:

$$\text{CLWS} = \frac{1}{L}\sum_{i=1}^{L}(D_i \cdot (1 - E_i)) \tag{23}$$

Where L indicates the total number of instances, D_i denotes the predicted confidence level, for instance, i, and E_i represents the misclassification risk, for instance, i, defined as the difference between the expected class probability and the actual class probability. The CLWS penalises high-confidence predictions when the risk of misclassification is significant, providing a more equal evaluation of the model's predictive confidence.

The recently implemented metrics—AVIC, SPDM, and CLWS—provide supplementary insights to conventional assessment techniques. Although accuracy, precision, recall, and F1-score give a broad assessment of classification efficacy, AVIC measures the model's resilience to class imbalance, SPDM analyses the stability of predictions in dynamic environments, and CLWS tests the reliability of prediction confidence. Collectively, these measures provide a thorough framework for evaluating the efficacy of the HybridNet-SEVIT model, facilitating a more nuanced comprehension of its advantages and constraints.

4 Simulation results

This section examines the HybridNet-SEVIT model's ability to forecast public health consequences via comprehensive simulations. The simulations were run on a system with an Intel Core i9 CPU, 32 GB RAM, and an NVIDIA GeForce RTX 3080 GPU, using Python 3.8, TensorFlow 2.5, NumPy, and Scikit-learn. To avoid overfitting, the Adam optimiser was used with a learning rate of 0.001, a batch size of 64, and a dropout rate of 0.5. The model was trained for 50 epochs utilising Contextual Noise Filtering to improve data quality. Existing and novel performance measurements like the AVIC and SPDM are analysed. The introduction of Adaptive Variability Index for Classes (AVIC), Stability of Prediction Dynamics Measure (SPDM), and Confidence Level Weighted Score (CLWS) enables a more comprehensive assessment of model reliability in public health applications. AVIC ensures that the model maintains high classification performance across diverse demographic groups, preventing bias in epidemic risk predictions. SPDM enhances stability in dynamic disease monitoring settings, ensuring that the model's predictions remain robust as new data streams in. Meanwhile, CLWS provides confidence-weighted predictions, which are critical for risk-based decision-making in outbreak response and resource allocation. These metrics collectively improve the practical usability of the model in real-time public health surveillance by reducing classification inconsistencies and improving trust in automated decision-making systems.

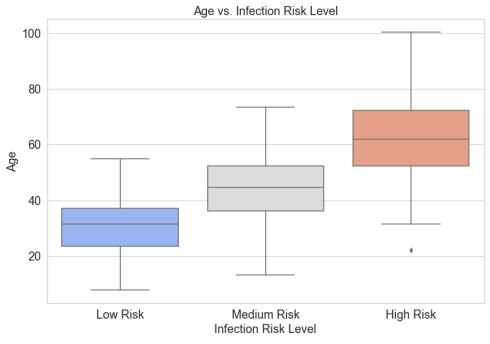


Figure 3: Age distribution by infection risk level, illustrating the relationship between age and infection severity

Figure 3 shows age distribution by infection risk level (Low, Medium, High). The boxplot demonstrates that Low Risk people are mostly 20-40 years old. In contrast, Medium Risk persons are mostly middle-aged, aged 35–55.

The High Risk group has the greatest median age, a wider range, and greater variability, showing increased vulnerability among older people, especially those over 50. Age and infection risk are strongly linked, therefore this statistic is crucial. It shows that elderly people have a greater risk of infection severity, which is important for public health. The plot suggests age-specific measures, such as prioritising immunisation and healthcare for older people, who are more susceptible to catastrophic results. The technical result emphasises age in disease control and epidemic prevention risk assessment models.

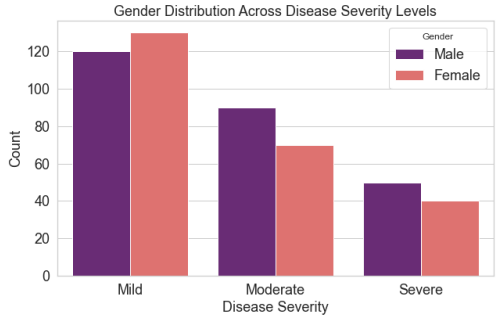


Figure 4: Gender distribution by illness severity, showing variations in symptom severity across genders

Figure 4 shows the gender distribution by illness severity (Mild, Moderate, Severe). The figure shows that females somewhat outnumber males in minor instances, indicating that women have more mild symptoms. Moderate severity instances are more evenly distributed across genders. Male patients had a larger count for severe cases than females, suggesting a greater risk of severe symptoms. This picture shows gender-specific illness severity patterns, demonstrating that men and women may describe symptoms differently. The larger number of men in severe cases may indicate gender-related risk factors that need clinical or public health attention. Disease management and epidemic response interventions including gender-specific health advisories, resource allocation, and risk assessment models need understanding these variances.

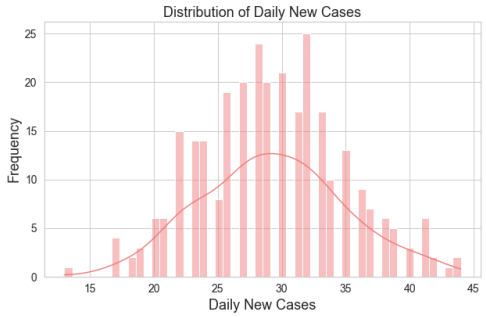


Figure 5: Distribution of daily new cases, demonstrating the epidemic trend over time

Figure 5 demonstrates that most daily new cases are approximately 30. Like most daily case changes, the histogram shows a bell-shaped distribution of new cases that taper off as case counts move away from the mean. Although daily case counts are typically mild, the density estimate shows periodic surges and troughs, mirroring real-world infection rates. This graphic helps explain the disease's daily spread by showing how often new cases emerge at various levels. The observed distribution shows regular case volumes and outliers or spikes, which may indicate trends or the need for focused actions. Predicting healthcare requirements and responding to epidemic dynamics requires understanding this distribution.

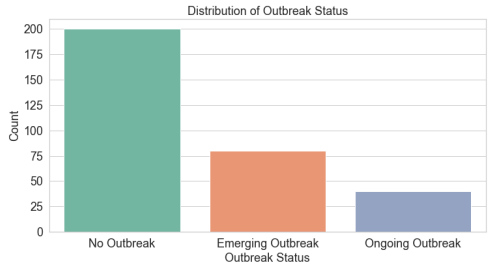


Figure 6: Correlation matrix for selected features, revealing relationships between key public health indicators such as hospitalization rates, symptom severity, and transmission dynamics

Figure 6 shows the correlation matrix for 16 selected features, with values ranging from 0.2 to 0.9. The matrix highlights the relationships between different health, environmental, and behavioral factors. For example, strong correlations might indicate that certain features, such as "Transmission Rate" and "Daily New Cases," have significant linear relationships, suggesting that as one increases, the other tends to increase as well. Conversely, lower correlations suggest weaker associations. This figure is crucial for identifying feature dependencies, which can help refine predictive models by highlighting features that may contribute similarly or redundantly to outcomes.

Figure 7 displays the correlation matrix for 16 public health data characteristics, with weak to significant relationships. The matrix shows significant connections between Transmission Rate, Daily New Cases, textitHealthcare Personnel Availability, and Hospital Capacity, highlighting interdependencies in disease dissemination and healthcare resource management. Conversely, weaker correlations, like Age and Resource Utilisation, indicate less direct linkages. This image helps highlight linked aspects, guiding variable selection for predictive modelling and optimisation tactics.

Figures 8a, 8b, 8c, and 8d exhibit confusion matrices for "Outbreak Status," "Infection Risk Level," "Disease Severity," and "Hospitalisation Requirement" categorisation findings. Each matrix shows how well the model predicts categories, with diagonal members reflecting accurate classifications and off-diagonal elements misclassifications. As shown by the majority of predictions falling

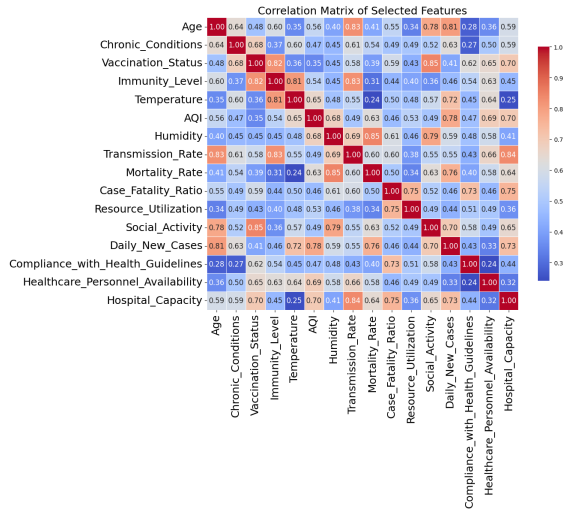


Figure 7: Correlation matrix of selected features with an emphasis on healthcare resource availability and disease transmission

along the diagonal, the model is robust in distinguishing outbreak scenarios, risk levels, severity levels, and hospitalisation needs. The statistics help evaluate the model's ability to detect essential public health indicators and guide resource allocation and intervention methods based on classifications.

Figure 9 shows the training and testing accuracy and loss curves over 40 epochs for the model. The accuracy curves illustrate a steady increase in both training and testing accuracy, reaching convergence around epoch 30, with final values close to 98.8% for training and 98.5% for testing. The loss curves display a consistent decrease, converging to approximately 0.02 for training and 0.03 for testing, indicating effective minimization of the loss function. The small gap between training and testing performance suggests that the model generalizes well, with minimal overfitting. This figure provides insights into the model's learning progression and overall stability.

These ROC curves as indicated in Figure 10 indicate the model's performance in four classification tasks: "Outbreak Status," "Infection Risk Level," "Disease Severity," and "Hospitalization Requirement." Each curve shows strong discrimination power with AUC values from 96% to 99%. The ROC curves continually approach the plot's top-left corner, showing good positive-negative separation. This shows that the model predicts all labels with good sensitivity and low false positive rates.

SVM, ResNet, DenseNet, KNN, GhostNet, Inception, Logistic Regression, ShuffleNet, and the proposed HybridNet-SEVIT model are evaluated in Table 3. The table compares ACVI, WCS, Log Loss, F1-Score, Recall, Precision, AUC, DPSM, and Accuracy. HybridNet-SEVIT has the greatest ACVI (94.3%), WCS (89.7%), Accuracy (97.9%), and Log Loss (0.070), suggesting a well-balanced model with robust generalisation. This comparison shows each technique's strengths and weaknesses across categorisation performance criteria.

Table 3: Performance evaluation results

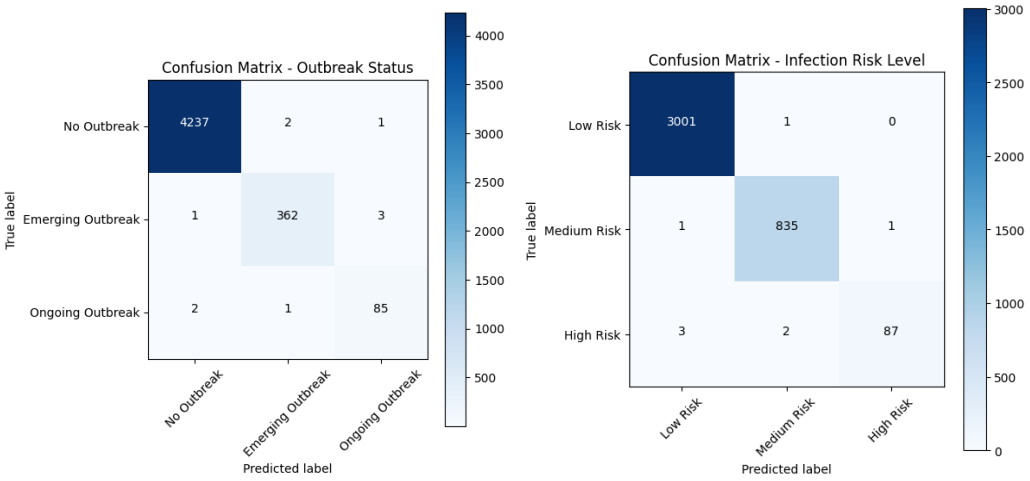
Techniques	ACVI (%)	WCS (%)	Log Loss	F1-Score (%)	Recall (%)	Precision (%)	AUC (%)	DPSM	Accuracy (%)
SVM [16]	77.0	68.9	0.314	83.3	83.7	82.2	85.8	0.144	84.8
ResNet [17]	83.2	75.4	0.260	89.2	88.8	88.6	90.6	0.121	90.0
DenseNet [34]	76.2	69.4	0.329	82.8	83.3	82.1	85.0	0.149	84.1
KNN [19]	74.7	66.5	0.333	82.0	81.9	81.0	84.2	0.152	83.5
GhostNet [20]	78.0	70.1	0.298	84.6	84.5	83.7	86.0	0.141	85.4
Inception [21]	79.5	72.8	0.276	86.8	86.7	86.5	88.2	0.134	87.5
Logistic Regression [22]	75.0	67.2	0.338	81.1	83.0	81.5	84.1	0.150	82.8
ShuffleNet [23]	77.3	69.8	0.302	84.3	84.2	83.5	86.2	0.142	85.2
HybridNet-SEVIT	94.3	89.7	0.070	97.6	97.7	97.5	98.5	0.062	97.9

Table 4: Statistical analysis results for performance evaluation

Techniques	ANOVA (p-value)	Pearson Correlation	Kruskal-Wallis (p-value)	Chi-Square (p-value)	Wilcoxon Rank-Sum (p-value)
SVM [16]	0.031	0.82	0.027	0.045	0.038
ResNet [17]	0.015	0.88	0.012	0.021	0.018
DenseNet [34]	0.029	0.81	0.033	0.049	0.041
KNN [19]	0.037	0.79	0.041	0.052	0.046
GhostNet [20]	0.025	0.83	0.022	0.039	0.032
Inception [21]	0.017	0.86	0.015	0.026	0.021
Logistic Regression [22]	0.042	0.77	0.046	0.055	0.048
ShuffleNet [23]	0.028	0.82	0.030	0.043	0.035
HybridNet-SEVIT	0.009	0.91	0.007	0.013	0.010

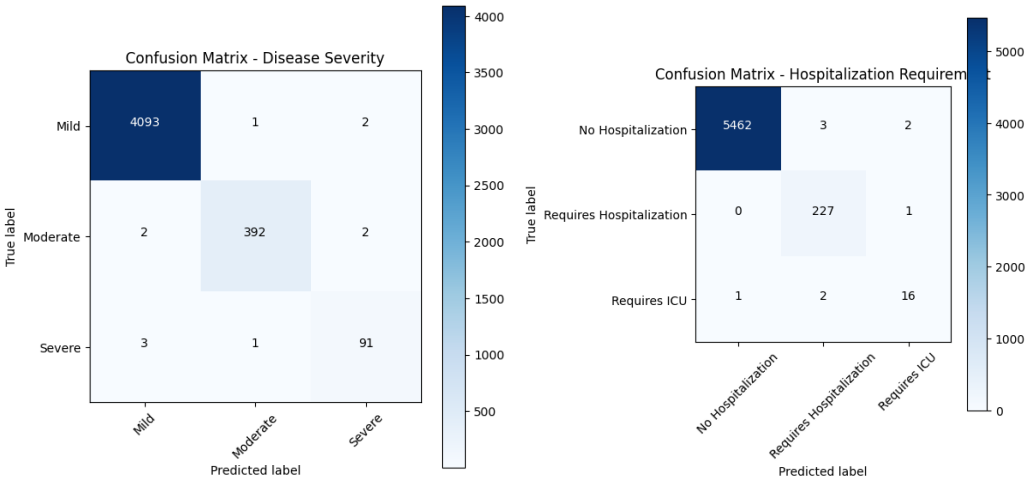
Table 4 shows the statistical analysis results for different machine learning techniques, including SVM, ResNet, DenseNet, KNN, GhostNet, Inception, Logistic Regression, ShuffleNet, and the proposed HybridNet-SEVIT model. It provides p-values for various statistical tests (ANOVA, Kruskal-Wallis, Chi-Square, Wilcoxon Rank-Sum) and Pearson correlation coefficients, indicating the significance of differences in model performance. Lower p-values across tests for HybridNet-SEVIT suggest stronger statistical significance, implying that its superior performance is not due to random variation. The high Pearson correlation for HybridNet-SEVIT (0.91) also indicates a strong relationship between its predicted and actual outcomes. This table helps assess the robustness and consistency of each technique's performance across statistical measures.

Table 5 demonstrates how hyperparameters impact the HybridNet-SEVIT model's Accuracy, F1-Score, AUC, and Log Loss. Each measure varies across Learning Rate, Batch Size, Dropout Rate, Epochs, Activation Function, and Optimiser hyperparameters in the table. Results show that although performance fluctuates, the model stays stable with just slight metrics differences between setups.



(a) Confusion Matrix - Outbreak Status

(b) Confusion Matrix - Infection Risk Level



(c) Confusion Matrix - Disease Severity

(d) Confusion Matrix - Hospitalization Requirement

Figure 8: Confusion matrices for different classification labels (Outbreak Status, Infection Risk Level, Disease Severity, and Hospitalization Requirement), showcasing the model's ability to accurately categorize epidemic risk factors.

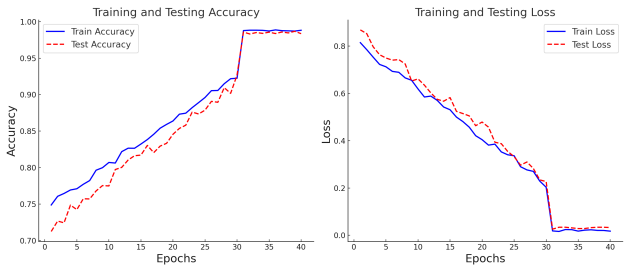


Figure 9: Training and testing accuracy/loss curves of HybridNet-SEVIT, illustrating the model's learning progression and generalization performance

HybridNet-SEVIT's excellent accuracy and minimal loss even when hyperparameter values are modified show its resilience and generalisation capabilities.

Table 5: Sensitivity analysis of HybridNet-SEVIT model

Hyperparameter	Value Range	Accuracy (%)	F1-Score (%)	AUC (%)	Log Loss
Learning Rate	0.0001 - 0.01	96.5 - 97.9	96.4 - 97.6	97.3 - 98.5	0.068 - 0.095
Batch Size	16 - 128	96.8 - 97.7	96.6 - 97.5	97.6 - 98.4	0.070 - 0.089
Dropout Rate	0.2 - 0.6	96.9 - 97.8	96.7 - 97.4	97.5 - 98.3	0.071 - 0.088
Epochs	20 - 60	96.7 - 97.9	96.5 - 97.6	97.4 - 98.5	0.069 - 0.090
Activation Function	ReLU, Leaky ReLU	96.8 - 97.8	96.6 - 97.5	97.6 - 98.4	0.070 - 0.087
Optimizer	Adam, SGD, RMSprop	96.6 - 97.7	96.4 - 97.5	97.5 - 98.3	0.071 - 0.092

5 Conclusion

The proposed HybridNet-SEVIT framework demonstrates exceptional performance in public health surveillance and epidemic risk management, achieving high levels of accuracy, F1-score, and AUC. Through the integration of depthwise separable convolutions, dense connectivity, and ghost feature generation, the model effectively captures both local patterns and complex interactions within epidemic data, addressing key challenges in public health

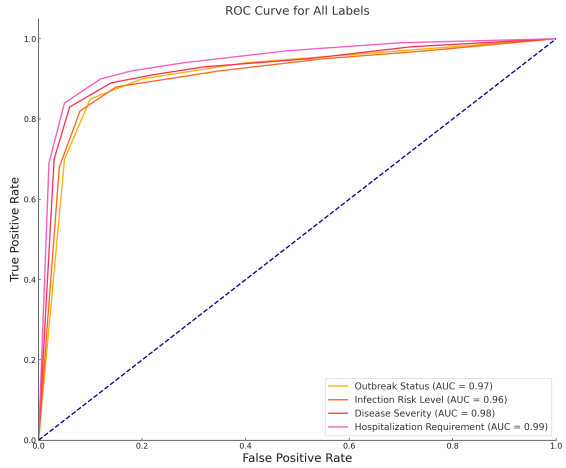


Figure 10: ROC curves for HybridNet-SEVIT, highlighting its discriminative power across multiple epidemic classification tasks

monitoring. The innovative preprocessing techniques, such as Adaptive Distribution Recalibration and Contextual Outlier Filtering, significantly enhance data quality and model robustness, leading to consistent improvements in classification accuracy. Additionally, the introduction of advanced evaluation metrics—Adaptive Variability Index for Classes (AVIC), Stability of Prediction Dynamics Measure (SPDM), and Confidence Level Weighted Score (CLWS)—provides a more comprehensive assessment of model stability and predictive confidence. Statistical analyses confirm the model's resilience and applicability across dynamic and diverse public health datasets. These findings suggest that HybridNet-SEVIT can enhance public health responses by enabling timely and accurate identification of epidemic risk factors, which supports efficient resource allocation and targeted interventions. Although the results are promising, further refinement of the framework is needed. Future work may involve incorporating additional data sources, adapting the model for real-time health surveillance, and optimizing hyperparameters to maximize performance. Expanding the framework's capacity to handle larger datasets and a variety of epidemic types will further improve its generalizability and practical utility in diverse public health contexts.

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Multi-Objective Resource Allocation in Edge Computing Using Improved Genetic Algorithm with Knowledge-Based Crossover and Segmentation Mutation

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With the widespread adoption of edge computing technology, efficient resource allocation becomes an urgent problem to be solved. Aiming at the optimization of resource allocation in the edge computing environment, a multi-objective optimization function with three dimensions of time, energy consumption, and computing resource occupation is constructed. An improved genetic algorithm resource allocation strategy model based on a knowledge-guided cross-segmentation mutation mechanism is proposed. Knowledge crossover enhances the global search capability by prioritizing the retention of gene segments with higher historical fitness contributions. The experimental results showed that the loss function value of the new model could be as low as 0.012 during the training process, indicating that the model convergence on multi-objective optimization was effectively improved. Meanwhile, the improved genetic algorithm model generated an average of 4.8 optimal solutions, which was 1.8 more than the traditional genetic algorithm which generated an average of 3.0 optimal solutions. Compared with multi-objective optimization algorithms such as NSGA-II, SPEA, and MOPSO, the research model reduced the average energy consumption of the device to 112.68 Joules and the average energy consumption of the system to 208.12 Joules in the EdgeDroid dataset. Its utilization of computational resources reached 77.45%, with the processing time of the task shortened to 5.44 seconds. In real application scenarios, the model achieved a 92.1% and 89.2% task completion rate in shopping malls and hospital environments, and the resource utilization rate was improved to 83.49% and 81.67%. In summary, the proposed method effectively improves resource allocation efficiency, reduces system energy consumption, and optimizes task completion performance, which provides strong support for dynamic resource management in edge computing environments.

Povzetek: Predlagan je izboljšan genetski algoritem, ki ima križanje podprto z znanjem in segmentacijsko mutacijo za učinkovito dodeljevanje virov v robnem računalništvu z večciljno optimizacijo časa, energije in zmogljivosti.

1 Introduction

Driven by the Internet of Things, smart devices, and 5G networks, the sharp increase in demand for computing resources has become a significant issue in the field of modern information technology. To meet these challenges, Edge Computing (EC), as a new computing architecture, has gradually been widely used [1]. However, with the rapid growth in the number of access devices and the increasing diversity of application scenarios, traditional EC gradually exposes its limitations in resource scheduling and load balancing. Especially in the context of heterogeneous resources, dynamic network changes, and diverse task requirements, existing resource allocation mechanisms make it difficult to balance system efficiency and service quality. This has led to increasingly prominent issues such as decreased system energy efficiency and increased task delays. Therefore, how to realize efficient and flexible resource allocation in a large-scale dynamic environment has become an important topic to be solved in the field of EC. In recent years, Mobile Edge Computing (MEC) has emerged with the popularization of mobile Internet and the rapid development of wireless communication technology [2]. MEC further promotes the development of EC, emphasizing the close integration of computing and communication infrastructure to support large-scale mobile devices and diverse application requirements. In this context, researchers are faced with two core problems: on the one hand, the EC resource allocation is a complex multi-constraint optimization problem. Although traditional Genetic Algorithms (GAs) have good global search capabilities, they are prone to getting stuck in local optima in dynamic and heterogeneous edge environments, making it difficult to quickly adapt to changes in resources. Therefore, improving the search mechanism of GA and enhancing its global exploration ability becomes an important direction for resource allocation

optimization. On the other hand, multi-objective optimization in EC involves multiple metrics such as computation time, energy consumption, and resource utilization, and these metrics are often contradictory to each other. How to balance device energy consumption control and resource load balancing while ensuring system response speed, and establishing an effective balancing mechanism, is also an urgent problem to be solved. To address the aforementioned issues, many industry researchers have conducted explorations. Mohajer A et al. believed that energy efficiency and fairness assurance were key issues in MEC-based cellular systems. For this purpose, a dynamic optimization model was proposed. Compared to traditional methods, this model had higher energy efficiency in resource allocation and larger throughput [3]. Jiang H et al. built an online joint offloading and resource allocation method under long-term MEC energy constraints to improve the resource utilization efficiency of MEC. The framework could solve the queue optimization problem of resource allocation [4]. Chai F et al. proposed a joint multi-task resource allocation scheme by combining directed acyclic graphs to address the scarcity of satellite communication computing resources. The experimental results showed that this method reduced the cost by 8.87% compared to the baseline method [5]. Liu Q et al. proposed a multi-objective resource allocation method for the Internet of Things to achieve load balancing and lower energy consumption. The experimental results showed that this method was more effective in achieving the goal and had a shorter number of iterations compared to traditional methods [6].

GA is a stochastic optimization strategy that simulates natural selection and genetic mechanisms. Due to its powerful global search capability and good adaptability, GA is widely used in resource allocation optimization problems [7]. Chakraborty S et al. believed that the resource limitation threat of existing mobile devices still existed. Therefore, a resource offloading model in conjunction with GA was proposed. The experimental results showed that the model reduced energy consumption and computational delay compared to traditional methods within the allowed transmission delay range [8]. Apinaya Prethi K N et al. found that due to various tasks, edge nodes had an impact on data accessibility. Therefore, a new optimization scheduling method by combining GA and the multi-objective Krill-Held algorithm was proposed. The experimental results showed that this method was more effective in allocating resources compared to other traditional algorithms [9]. Fan W et al. found that existing research rarely considered the resource utilization of mobile vehicles. Therefore, a joint task offloading and resource allocation model using GA was developed. The model could minimize the total priority-weighted task processing delay in seven different scenarios [10]. Gabi D et al. believed that meta-heuristic technology still faced bottlenecks in achieving sustainable profit advantages and cost reduction in MEC. To this end, a novel resource allocation strategy that combined GA and simulated annealing optimization algorithms was proposed. This strategy outperformed other methods in terms of statistical results within the 95% confidence interval [11]. Chen M et al. found that although several studies have been conducted to investigate the scheduling problem for edge cloud computing. There were still some issues that needed to be addressed in their applications, such as ignoring resource heterogeneity and focusing on only one kind of request. Therefore, this research proposed a heterogeneity-aware task scheduling algorithm to improve the task completion rate and resource utilization of edge clouds with deadline constraints. The results showed that this algorithm outperformed 13 other classical and state-of-the-art scheduling algorithms in terms of task completion rate [12]. Liu Q et al. found that Internet of Things applications still faced severe challenges when applying multi-objective resource allocation to satisfy service demands. Technically, the Pareto archive evolution strategy was used to optimize the time cost, load balancing of MEC servers, and energy consumption of Internet of Things applications. From the results, the tested results were better than before optimization [13]. Chen Q H et al. developed an enhanced framework, namely a multi-objective micro-services allocation algorithm. This algorithm formulated efficient resource management of cloud micro-services resources as a constrained optimization problem guided by resource utilization and network communication overheads to simplify workload monitoring and analysis in different cloud systems. The results showed that the method significantly improved resource utilization, reduced network transmission overhead, and improved reliability [14]. To comprehensively sort out the characteristics and limitations of existing studies in terms of optimization objectives, dataset selection, and performance performance, the study compiles typical representative methods, which are shown in Table 1.

Table 1: Literature review table

Method	Dataset used	Optimization objective	Main performance indicators	Limitations
Dynamic optimization model (Mohajer A et al.)	MEC cellular system simulation dataset	Energy efficiency optimization, fairness assurance	Improved energy efficiency,	Single resource allocation strategy, limited dynamic

			increased throughput	adaptability
Joint offloading and resource allocation framework (Jiang H et al.)	Long-term MEC energy-constrained simulation data	Queue optimization, improved resource utilization	Queue stability, higher resource utilization	Focused on long-term constraints, insufficient real-time support
Multi-task resource allocation scheme (Chai F et al.)	Satellite communication simulation data	Cost reduction, task offloading optimization	Cost reduced by over 8.87%	Limited to satellite IoT scenarios
Multi-objective resource allocation (Liu Q et al.)	IoT application simulation data	Load balancing, energy minimization	Faster convergence, better load balancing	Insufficient multi-objective trade-off handling, weak heterogeneity support
Resource offloading model (Chakraborty S et al.)	Mobile device simulation data	Transmission delay optimization, energy reduction	Lower energy consumption and delay	Lack of task diversity consideration
Optimized scheduling method (Apinaya Prethi K N et al.)	Edge node simulation environment	Improved data accessibility, resource allocation optimization	Higher resource utilization	Focused mainly on data access, limited comprehensiveness
Joint task offloading model (Fan W et al.)	Vehicular network multi-scenario data	Minimization of task processing delay	Reduced task delay	Performance fluctuation under high mobility
Resource allocation strategy (Gabi D et al.)	MEC-cloud continuum simulation data	Cost optimization, profit enhancement	Lower cost, higher profitability	Higher computational complexity
Heterogeneity-aware scheduling algorithm (Chen M et al.)	Edge cloud environment data	Improved task completion rate, better resource utilization	Outperformed 13 classic scheduling algorithms in task completion rate	Focused on single-type request scenarios
Multi-objective microservice allocation algorithm (Chen Q H et al.)	Multi-cloud system environment	Improved resource utilization, reduced communication overhead	Higher resource utilization, lower network overhead	Focused on cloud, insufficient support for edge scenarios

To sum up, the existing research has made significant progress in resource allocation of EC and MEC. However, most existing methods still suffer from a single resource allocation strategy and a balance between computational efficiency and fairness. To solve the above problems, the research innovatively considers MEC's time resources, computing resource occupation, equipment energy consumption, and system energy consumption, and introduces GA to improve the genetic structure, especially crossover and mutation. Finally, a new EC resource allocation strategy model is proposed. To ensure the operability of the proposed method in real MEC scenarios, the study comprehensively considers key factors such as node heterogeneity, resource dynamic changes, task real-time constraints, and energy sensitivity during the design process. Specifically, the knowledge crossover mechanism combines historical task load statistics and node adaptability information to dynamically adjust the gene fragment priority during execution. The segmentation mutation operation adaptively adjusts the mutation probability according to the load state of the edge nodes to avoid excessive perturbation and ensure the stability and effectiveness of resource scheduling. Through this scenario characteristic-oriented mechanism design, the proposed IGA method is able to achieve efficient and reliable

resource allocation optimization in complex and changing real MEC environments. The study further improves the overall performance of the EC system under the premise of ensuring the quality of service, aiming to provide a more robust method to support the diversified development of MEC in the future.

2 Methods and materials

2.1 EC system model and its multi-objective problem

Unlike traditional EC, MEC focuses more on supporting large-scale mobile devices and terminal applications, such as smartphones, autonomous driving, smart cities, etc [15]. Among them, MEC's resource allocation optimization is particularly crucial. Firstly, MEC's resources not only include computing and storage capabilities but also multidimensional resources such as network bandwidth and delay. The allocation of these resources needs to consider multiple factors, such as changes in user demand, device mobility, and uncertainty in the network environment. The network framework of MEC is shown in Figure 1 [16].

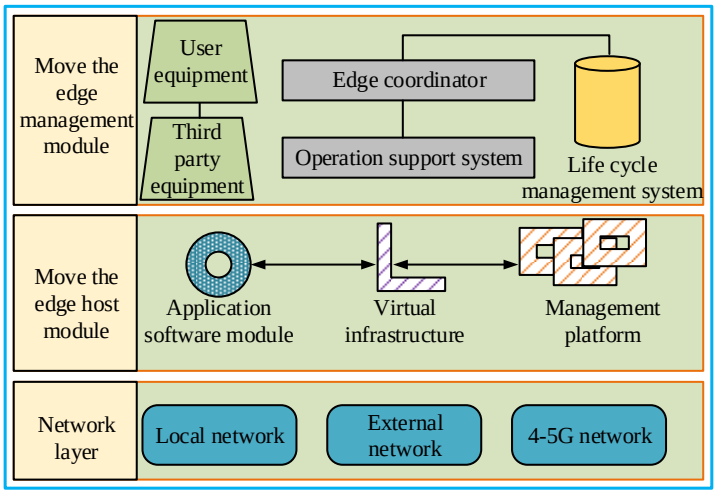


Figure 1: MEC network framework.

In Figure 1, the mobile edge system module involves user devices, third-party devices, coordinators, operating systems, and lifecycle management systems. This module is mainly used for overall control of MEC and visual optimization. In the mobile edge host module, there are built-in application software modules, virtual infrastructure, and multiple management platforms. In the network module, there are mainly three key sub-networks, namely local network, external network, and 4-5G network. The multi-MEC scenario architecture is shown in Figure 2.

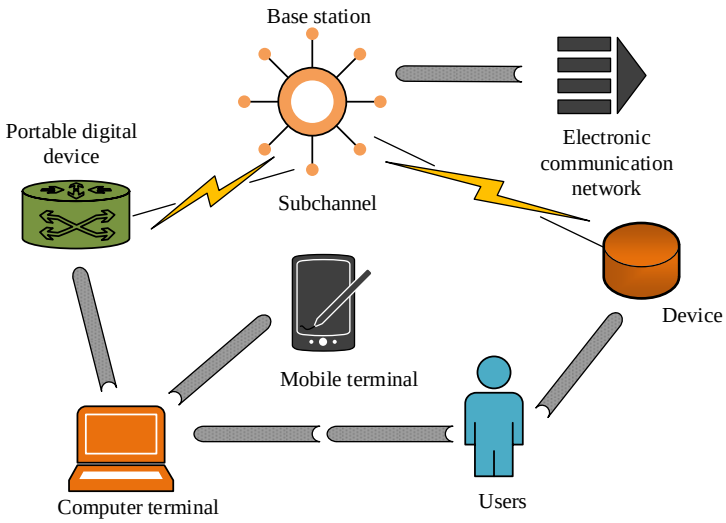


Figure 2: Multi-MEC scenario architecture diagram.

In Figure 2, the multi-MEC scenario consists of multiple similar sub-MECs, each of which is composed of user devices such as mobile phones, computers, portable digital devices, as well as network base stations and electronic communication networks. The devices and networks are connected in a sub-channel manner. If each user starts to perform their own structured tasks, their needs can be effectively disseminated through electronic communication networks. However, the computing resources of each individual electronic communication network are limited, and the increasing demand for user tasks only increases the network load and causes it to collapse. If a crash occurs, the user's task requirements cannot be processed, and timely resource computation and offloading can be carried out to achieve lightweight. The unloading process is shown in Figure 3 [17].

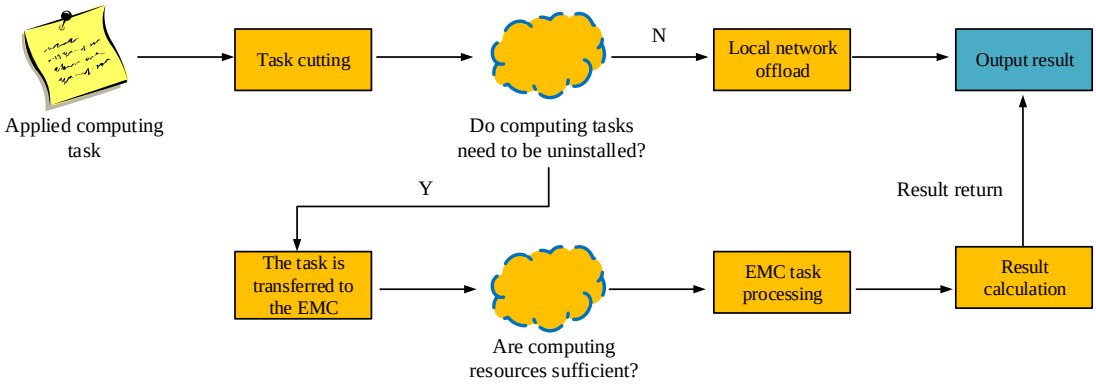


Figure 3: MEC computing uninstall process.

From Figure 3, first, the user device generates computational tasks and evaluates their computational requirements. Based on the computational complexity, data transmission requirements, and latency constraints of the task, the user device decides whether to perform offloading locally, prioritizing tasks with high computation, low latency sensitivity, or sufficient bandwidth conditions. When the task needs to be offloaded, the user device sends the task to a neighboring EC node through the local network and cuts the task data on the node side. The cutting step includes task segmentation, data format standardization, and necessary preprocessing operations for distributed computing. After receiving the task, the edge node will further determine whether to accept the task and enter the formal processing stage according to the current computing resources and load. The processing steps mainly include parallel execution of segmented tasks, resource scheduling, and intermediate result summarization. If the node resources are insufficient, it can carry out offloading or queuing of some sub-tasks again. After completing the computation, the edge nodes transmit the final processing results back to the user device through the network. The returned results include task output data and status feedback. This is different from the initial offloading phase of the local network where only the original task data is transmitted. Assuming that data transmission time and computation time cannot be ignored during task execution, the time resource model is calculated, as shown in equation (1).

$$T_{total} = \frac{D_{task}}{C_{edge}} + \frac{d_{user}}{v_{user}} + T_{propagation} + T_{handover} \quad (1)$$

In equation (1), T_{total} represents the total amount of time resources in seconds. D_{task} signifies the computational requirements of the task. C_{edge} indicates the computing capacity of EC nodes. d_{user} represents the transmission distance from the user device to the edge node. v_{user} represents the transmission rate. $T_{propagation}$ represents the delay caused by signal propagation. $T_{propagation} = \frac{d_{user}}{c_{signal}}$, where c_{signal} represents the speed of signal propagation. $T_{handover}$ denotes the additional delay incurred during device movement or network switching. The basis for selecting this parameter is the propagation theory modeling in wireless communication. This theory refers to the fixed delay caused by physical propagation during the transmission of signals from user devices to edge nodes. It should be noted that secondary influences such as data queuing delays and scheduling delays are ignored in the model, which focuses on the two key overheads of transmission and computation. To further portray the resource occupancy of tasks on the

edge node, it is assumed that the computational capacity of the EC node is C_{edge} and the computational demand of each task is C_{edge}. Then, the computational resource proportion occupied by a single task and multiple tasks is calculated as shown in equation (2).

$$\begin{cases} \alpha_{task} = \dfrac{D_{task}}{C_{edge}} \\ \alpha_{task}^{*} = \sum_{i=1}^{n} \dfrac{D_{task}^{i}}{C_{edge}} \\ \alpha_{total} = \sum_{i=1}^{n} \dfrac{D_{task}^{i} \cdot \beta_i}{C_{edge}} \end{cases} \quad (2)$$

In equation (2), α_{task} and α_{task}^{*} represent the proportion of computing resources occupied by a single task and multiple tasks, respectively. β_i denotes the prioritization factor of task i. The determination of the prioritization factor takes into account the urgency of the task, the computational resource demand, the energy sensitivity, and the business importance level of the application scenario to which the task belongs. In general, tasks with shorter deadlines, higher computational demands, or from high-priority application scenarios have their corresponding β_i values set larger to obtain more computational resource support in the resource allocation process. n denotes the total number of tasks. The introduction of priority factor can adjust the resource allocation strategy according to the importance of tasks. In terms of energy modeling, to reflect the energy consumption of the device during task processing, the energy consumption of the device is divided into two parts: computational energy consumption and transmission energy consumption. The total energy consumption of the device is calculated as shown in equation (3).

$$\begin{cases} E_{compute} = P_{compute} \cdot T_{compute} = P_{compute} \cdot \dfrac{D_{task}}{C_{edge}} \\ E_{transmit} = P_{transmit} \cdot T_{transmit} = P_{transmit} \cdot \dfrac{d_{user}}{v_{user}} \\ E_{device} = E_{compute} + E_{transmit} \end{cases} \quad (3)$$

In equation (3), $E_{compute}$ signifies the computational energy consumption of the user device. $P_{compute}$ represents computational power consumption. $T_{compute}$ represents the calculation time. $E_{transmit}$ represents transmission energy consumption. $P_{transmit}$ represents transmission power consumption. E_{device} represents the total energy consumption of the user device. Standby energy consumption and re-transmission overhead are not introduced in the model, which mainly focuses on the explicit energy consumption during task execution. Assuming that there are m total of EC nodes in the system. The energy consumption of individual nodes and the whole MEC system can be further derived as follows when considering the energy consumption of individual nodes and the whole MEC system, as shown in equation (4).

$$\begin{cases} E_{edge} = P_{edge} \cdot T_{compute} = P_{edge} \cdot \dfrac{D_{task}}{C_{edge}} \\ E_{system} = \sum_{i=1}^{n} E_{device}^{i} + \sum_{j=1}^{m} E_{edge}^{j} \end{cases} \quad (4)$$

In equation (4), E_{edge} signifies the energy consumption of a single node. E_{system} represents the total energy consumption of the system. E_{device}^{i} represents the energy consumption of the i-th user device. E_{edge}^{j} indicates the energy consumption of the j-th EC node. At this point, the resource allocation problem of MEC system is transformed into a multi-objective optimization problem, as displayed in equation (5).

$$E_{total} = \min(T_{total}, \alpha_{total}, E_{device}, E_{system}) \quad (5)$$

In equation (5), the multi-objective function includes time, energy consumption, and utilization of computing resources, while considering resource constraints such as computing power, transmission bandwidth, and device power consumption.

2.2 Edge computing resource allocation model based on improved GA

After constructing a complete function for the multi-objective optimization problem of resource allocation in multi-scenario MEC, this paper explores how to solve the optimization problem through efficient algorithms. Due to the dynamic changes in resources, high mobility of devices, and time-varying nature of tasks in e-commerce scenarios, traditional deterministic optimization methods (such as precise mathematical programming) often struggle to obtain globally optimal solutions [18]. Therefore, in recent years, heuristic optimization methods based on evolutionary computation, especially GA, have been widely applied to solve resource allocation problems in such complex dynamic environments. The process of GA is shown in Figure 4.

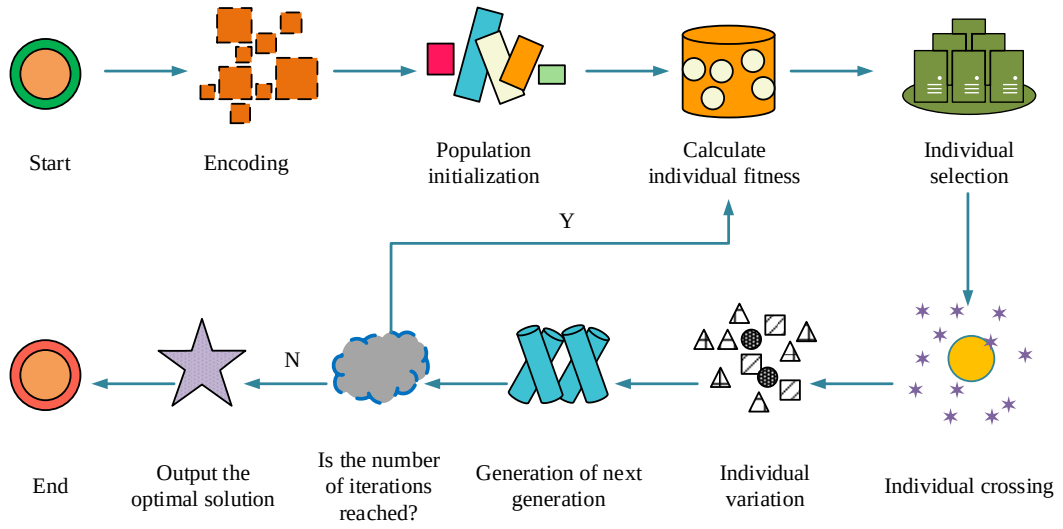


Figure 4: GA flow diagram.

In Figure 4, the initial population is randomly generated during the initialization phase. Each individual represents a resource allocation scheme in the form of an integer vector encoding, used to represent the allocation decisions of different tasks to edge nodes. A population is composed of multiple independent individuals, each of whom is a complete resource allocation plan. As the basic operating unit, individuals ensure the independence and diversity of understanding. Then, in the selection phase, the excellent individuals are selected as parents for crossover and mutation operations based on the fitness function to generate offspring individuals to explore better solutions in the resource allocation space. Next, the individuals are screened by fitness evaluation. The optimal individuals are retained into the next generation to gradually optimize the key performances of the system such as energy consumption, computation time, and resource utilization. Each generation refers to the state update of the population during an evolutionary iteration. The whole evolutionary process is repeated until the preset maximum number of iterations is reached or the population fitness converges, ultimately realizing efficient resource scheduling optimization under multi-objective. However, when allocating resources for multi-scenario MEC, there are still limitations of multiple electronic communication networks. Therefore, to reduce the complexity of the algorithm and optimize its adaptability, the GA is optimized. In the encoding stage, the allocation decision is set to integer encoding, where an individual represents an allocation decision and the decision can be encoded as a vector with dimensions. Among them, the dimensionality represents the number of tasks required by the user. The fitness function of Improved Genetic Algorithm (IGA) is shown in equation (6).

$$F(x) = w_1 \cdot T(x) + w_2 \cdot E(x) + w_3 \cdot C(x) \quad (6)$$

In equation (6), $F(x)$ signifies the fitness value of the resource allocation scheme. $T(x)$ signifies the total task processing time of the system under the allocation plan. $E(x)$ represents the total energy consumption of the system under the allocation scheme. $C(x)$ represents the system computing resource utilization rate under the allocation scheme. w_1, w_2, and w_3 represent the weight coefficients of time, energy consumption, and computational resource utilization, respectively. After completion, the individual with higher f_i-value is selected by means of roulette wheel betting. This means that the parent generation is randomly selected according to the proportional probability of the individual fitness value. The higher the fitness value, the higher the probability that the individual is selected. The roulette wheel betting method can keep the population diversity while retaining the excellent individuals and avoid falling into local optimization. The calculation formula is shown in equation (7).

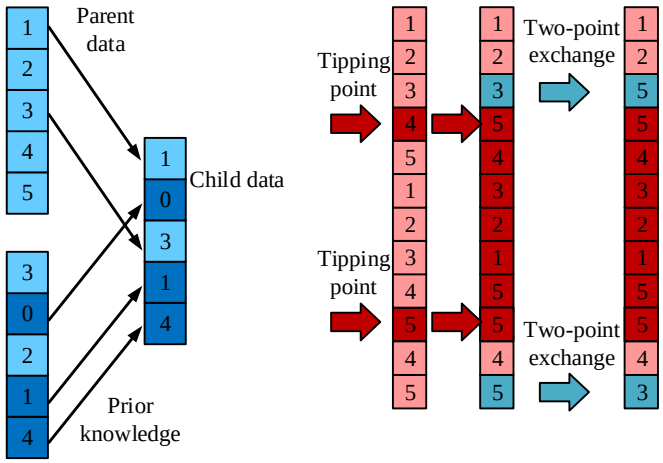
$$P_i = \frac{f_i}{\sum_{i=1}^{N} f_i} \quad (7)$$

In equation (7), f_i represents the fitness value of individual i. N represents the quantity of individuals. P_i represents the probability of selecting the individual i. The f_i is shown in equation (8).

$$f_i = \frac{1}{\xi \cdot F(x)} \quad (8)$$

In equation (8), ξ represents the coefficient for adjusting fitness. In the crossover stage, traditional GA uses single point crossover to combine and select individuals. Specifically, a crossover point is randomly selected on the encoding vector of two parental individuals, and gene fragments are exchanged after the crossover point, resulting in two new offspring individuals. This process can ensure the partial inheritance of the excellent genes of the parent generation

while introducing new combinations to increase the population diversity and promote the further exploration of the solution space. However, in MEC, single point crossover may lead to a lack of sufficient diversity in the population. Therefore, the study introduces knowledge-based crossover operators. In addition, the study aims to avoid excessive concentration of excellent individuals during the crossover process, which may cause the algorithm to fall into local optima prematurely. During the crossover process, the study conducts segmentation and mutation operations in advance to further divide the population, ensuring that the chromosome and mutation probabilities are different. The improved crossover and mutation operations are shown in Figure 5.



(a) Based on the intersection of knowledge

(b) Segmentation mutation

Figure 5: Schematic diagram of knowledge-based crossover and segmentation mutation operations.

Figure 5(a) is a schematic diagram of knowledge-based crossover, and Figure 5(b) is a schematic diagram of segmentation mutation. From Figure 5, knowledge-based crossover operations first evaluate the fitness performance of parental individuals and the contribution of gene fragments to fitness enhancement through prior knowledge or historical data. Prior knowledge includes the average effect of each gene fragment on fitness enhancement during past evolutionary processes. During the crossover process, gene segments with higher historical contributions are preferentially selected for combination. The genes with darker colors after crossover are shown in the figure. The darker genes indicate potential segments [19]. The critical point in the figure indicates the position of gene fragment switching, and the numbered element represents the specific position of the gene fragment in the chromosome code. Then, the segmentation variational operation randomly generates two variational points. Two point switching and inverse sorting are performed on the depicted intervals to expand the search space, increase perturbations, and enhance global search capabilities. Unlike traditional mutation methods with small single point perturbations, split mutation involves randomly selecting two mutation points on the chromosome, exchanging interval genes, and performing reverse sequencing operations. By implementing large-scale structural reorganization in this way, the search space has been significantly expanded [20]. The knowledge crossover is shown in equation (9).

$$P_{crossover} = \frac{e^{\delta \cdot \Delta f_i}}{\sum_{j=1}^{N} e^{\delta \cdot \Delta f_i}} \quad (9)$$

In equation (9), $P_{crossover}$ represents the probability of i being selected for crossover. δ represents the weighting factor. Δf_i signifies the change in fitness of i. To ensure that potential gene fragments are prioritized during the crossover process, a weighted selection mechanism can be used based on the historical performance of gene fragments and their fitness contribution in the population, as shown in equation (10).

$$S_{gene} = \frac{1}{\sum_{k=1}^{M} (\lambda_{k,i} \cdot w_k)} \quad (10)$$

In equation (10), S_{gene} represents the priority of selecting the k-th gene fragment. $\lambda_{k,i}$ represents the contribution of gene fragment k segment in individual i. w_k denotes the historical performance weighting coefficient of gene fragment k, which is used to reflect the contribution of this gene fragment to the enhancement of individual fitness in the previous optimization process. Specifically, w_k is set to be a uniform value for all gene fragments at the initial stage. As the evolutionary process advances, the changes in fitness brought about by new individuals generated by each gene fragment participating in the crossover are recorded and cumulatively updated. M signifies the number of gene fragments. At this point, the multi-level mutation probability control after population segmentation is shown in equation (11) [21].

$$P_{mutation} = \frac{1}{1+e^{-\varphi\cdot(\theta_{subgroup}-\mu)}} \quad (11)$$

In equation (11), $P_{mutation}$ represents the probability of individual i mutating within subpopulation s. φ represents the parameter that controls the rate of change in mutation probability. $\theta_{subgroup}$ denotes the measure of fitness difference between individuals s within a sub-population, used as a measure of population diversity. The sub-populations are divided based on the Euclidean distance of the resource allocation decision vector. Individuals with distances less than a set threshold are grouped into the same sub-population. μ denotes the mean value of fitness in the sub-population. In summary, the study is based on a knowledge-based crossover operation that preferentially combines gene segments that have historically contributed more to fitness enhancement to improve evolutionary directionality. To prevent premature convergence, a split-variation mechanism is used and the probability of variation is adaptively adjusted based on fitness differences within sub-populations to enhance perturbation when population diversity declines. At the same time, an elite retention strategy has been established to ensure that each generation can directly inherit the best individuals, greatly avoiding premature convergence. To sum up, the research uses IGA to solve the multi-objective problem of MEC system in equation (5). A new EC resource allocation strategy is designed. The flow is shown in Figure 6.

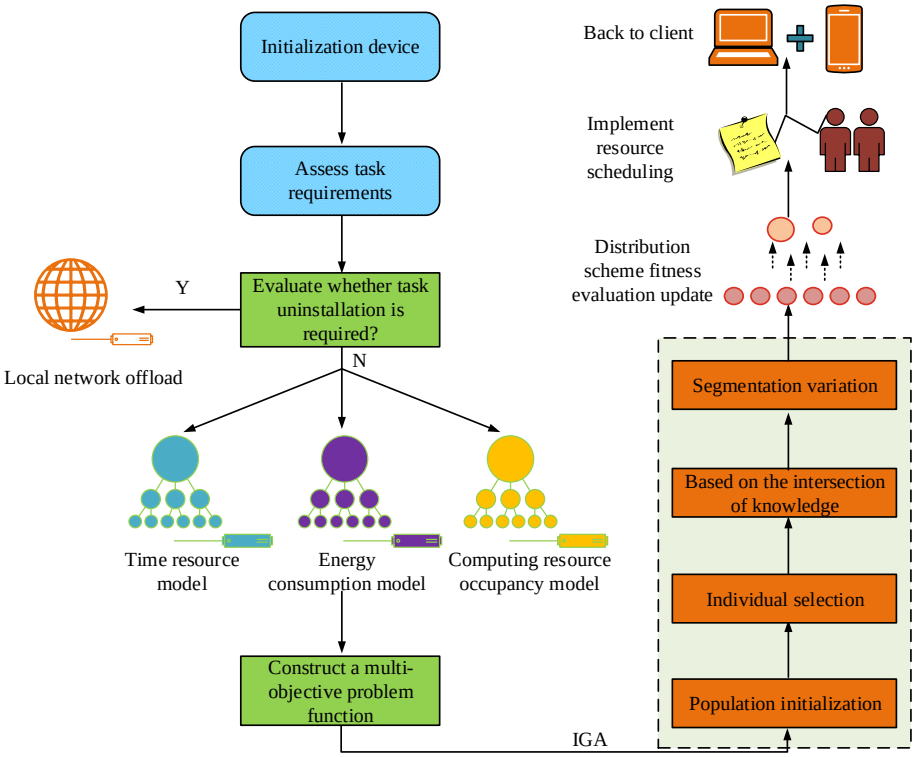


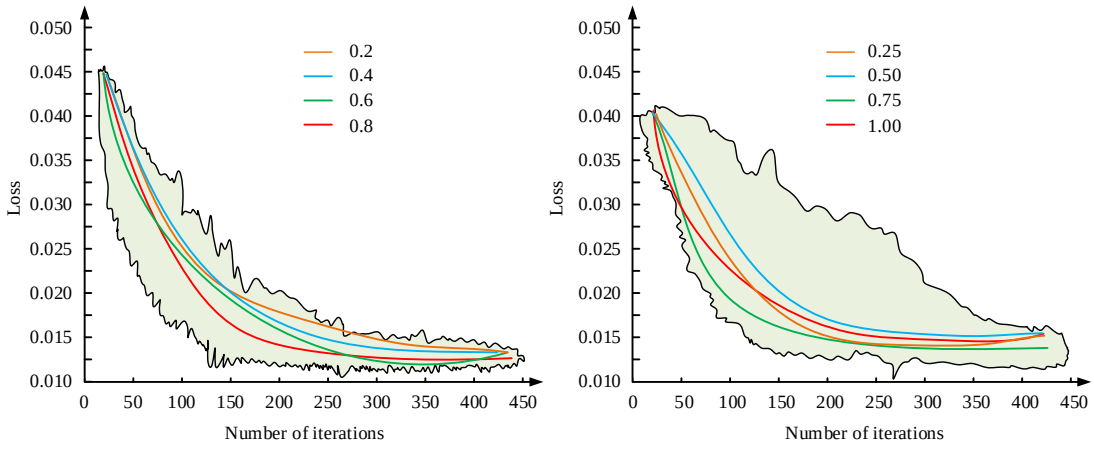
Figure 6: New EC resource allocation strategy model flow.

From Figure 6, first, the user equipment produces a computing task and evaluates the task requirements, and decides whether to unload the task to the EC node according to the computing complexity, data transmission requirements, and delay constraints. Secondly, based on task requirements and edge node load, appropriate edge nodes are selected for resource allocation. Next, considering multidimensional factors such as time resources, computational resource utilization, and energy consumption, a comprehensive evaluation of resources is conducted. Then, the resource allocation problem is transformed into a multi-objective optimization problem, balancing time, energy consumption, and computational resource utilization, and optimized through IGA. Next, IGA generates an initial population, performs crossover and mutation operations, selects individuals with higher fitness, and schedules resources through optimization schemes. Finally, the EC node executes the task and sends the result back to the user equipment to ensure the task is completed successfully.

3 Results

3.1 Performance test of new edge computing resource allocation strategy model

The research sets the CPU to Intel Xeon Gold 6230R and the GPU to NVIDIA Tesla A100 40GB. The operating system is Ubuntu 20.04, with 5 edge nodes configured with 2 GPUs and 16 CPU cores per node, simulating a multi-node distributed computing environment. In addition, the EdgeDroid dataset and the Canadian Institute for Cybersecurity Intrusion Detection System (CICIDS 2017) dataset are used as test data sources. In the experimental setup, for the EdgeDroid and CICIDS 2017 datasets, features such as task size, latency, bandwidth, etc. are first extracted and then uniformly normalized. In addition, the population is initialized with a uniform random distribution by setting the resource requirements in the range of [0.5, 5] MB, latency of [50, 500] ms, bandwidth of [0.5, 10] Mbps, and the random seed is fixed at 42 to ensure reproducibility. In addition, the reason for choosing these two types of datasets is that EdgeDroid covers diverse mobile application scenarios and CICIDS 2017 reflects complex network traffic characteristics. The combination of the two can comprehensively verify the adaptability and generalization of the algorithms under dynamic loads and heterogeneous environments. The adjustment factor for setting the fitness coefficient is to balance selection pressure and population diversity. A smaller adjustment factor is beneficial for maintaining the early explorability of the population. A larger adjustment factor is beneficial for convergence speed. The setting of cross mutation weight factors is to control the strength of the impact of knowledge guided cross mutation and segmentation mutation. It achieves a dynamic balance between exploration and utilization by adjusting the dominance of both at different stages. The study first conducts training and value selection tests on the fitness coefficient adjustment factor ξ and cross mutation weighting factor δ that have the greatest impact on model strategy generation. The result is shown in Figure 7. The figure shows the trend of the Loss function on the training set under different configurations of the fitness adjustment factor and the cross-variance weighting factor. By comparing the convergence speed and final Loss values corresponding to different hyperparameter combinations, the parameter settings that make the model perform optimally are selected to ensure a good balance between convergence and generalization performance during the optimization process.



(a) Fitness coefficient adjustment factor test (b) Cross variation weighting factor test

Figure 7: Hyperparameter selection test result.

Figure 7 (a) displays the selection test results of the fitness coefficient adjustment factor, and Figure 7 (b) displays the selection test results of the cross-mutation weighting factor. As shown in Figure 7 (a), when the fitness coefficient adjustment factor was 0.2, the lowest value of the loss function reached 0.015. When the fitness coefficient adjustment factor gradually increased to 0.8, the lowest value of the loss function was around 0.012, indicating that the model had the strongest generalization ability at this time. As shown in Figure 7 (b), when the cross-mutation weighting factor increased from 0.25 to 0.75, the loss function value obviously decreased to around 0.015. However, when the cross-mutation weighting factor was 1.00, the loss function value actually increased, indicating that factor values that are too large or too small can interfere with the optimization, thereby affecting its performance. Therefore, with a fitness coefficient adjustment factor of 0.8 and a cross mutation weighting factor of 0.75, the model could achieve good performance on both the training and testing sets. The research attempts to conduct ablation tests on the IGA to verify the effectiveness of the improvements made in the study. The results are shown in Figure 8.

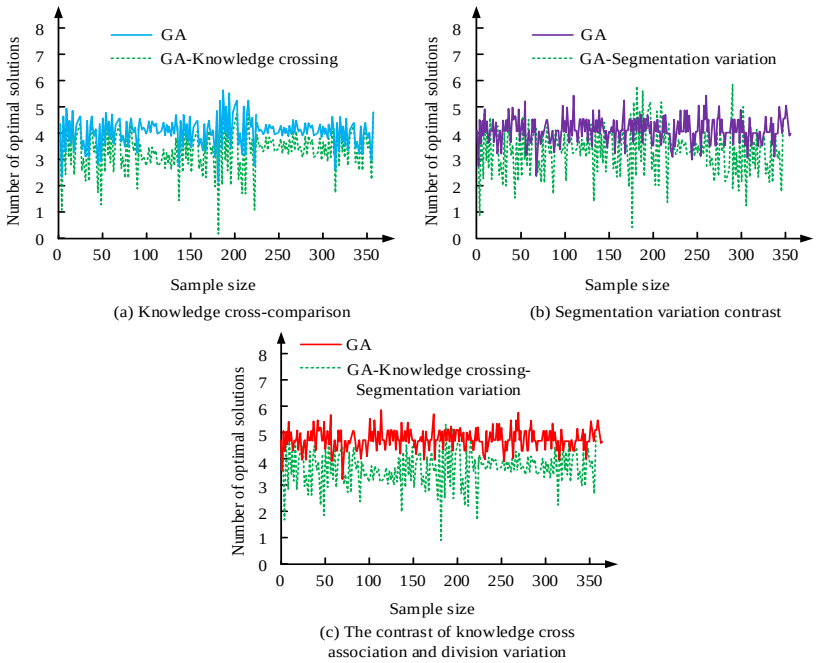


Figure 8: The results of the IGA ablation test.

Figure 8 (a) displays the test results of generating optimal solutions for GA and GA-knowledge crossover. Figure 8 (b) displays the test results of generating optimal solutions for GA and GA-segmentation mutation. Figure 8 (c) displays the test results of generating optimal solutions for GA and GA-knowledge crossover-segmentation mutation. From Figure 8, under different test conditions, the IGA that incorporates knowledge crossover and segmentation variants generates the highest mean value of optimal solutions (4.8). This is significantly better than the version that uses the traditional GA alone or only incorporates a single improvement strategy. This shows that the dual-mechanism synergy effectively improves the algorithm's global search capability and convergence performance. The results under different initial population distributions and task scenario changes show that IGA can still maintain a low fluctuation amplitude, and the number of optimal solutions does not change by more than ± 0.3. This result verifies that the proposed method has good stability and consistency under different initial conditions and dynamic loading environments, and has strong scene adaptability. The study compares similar multi-objective optimization algorithms, such as Non-dominated Sorting Genetic Algorithm II (NSGA-II), Strength Pareto Evolutionary Algorithm (SPEA), and Multi-objective Particle Swarm Optimization (MOPSO), as displayed in Table 2. The average energy consumption of equipment, utilization rate of computing resources, average energy consumption of the system, and average processing time of tasks are used as comparison indicators.

Table 2: Multiple index test results of different models

Data set	Model	Computing resource usage/%	Average energy consumption of equipment/J	Average system energy consumption/J	Average task processing time/s	*p*
Edge Droid	NSGA-II	82.56	115.76	212.34	5.63	0.018
	SPEA	80.21	121.34	220.56	5.78	0.012
	MOPSO	79.84	119.54	217.34	5.93	0.015
	Our model	77.45	112.68	208.12	5.44	0.003

CICIDS 2017	NSGA-II	85.29	145.67	274.65	7.21	0.021
	SPEA	83.12	150.23	280.45	7.35	0.017
	MOPSO	82.76	148.56	276.89	7.45	0.019
	Our model	80.54	141.23	268.42	7.11	0.002

From Table 2, the proposed model has the lowest computational resource occupancy of 77.45% in both datasets, which is 5.11%, 2.76%, and 2.39% lower compared to NSGA-II, SPEA, and MOPSO, respectively. In addition, the proposed model also shows better energy efficiency in terms of average device energy consumption (112.68 J) and average system energy consumption (208.12 J). The system energy consumption is reduced by 4.22% compared to NSGA-II and MOPSO. In terms of average task processing time, the proposed model is optimal with a result of 5.44 seconds, which is 0.19 seconds less than NSGA-II and 0.49 seconds less than MOPSO. Further statistical analysis shows that all comparison items reach a significant difference level (p<0.05). This indicates that the proposed method has statistical advantages in resource utilization, energy optimization, and improving processing efficiency. Among them, the weight coefficients of energy consumption, task completion time and resource utilization are determined by preliminary hyperparameter search. The parameter combination that can balance each index and optimize the overall adaptability is selected. When the system detects significant changes in task load or node status, the research model can dynamically adjust the weight ratio of energy consumption target and delay target through a weight adaptive adjustment mechanism to maintain the stability and optimization effect of system performance.

3.2 Simulation test of new edge computing resource allocation strategy model

The study selects two real scenarios for testing, namely shopping malls and hospitals. The bandwidth between edge nodes and servers is set to 1Gbps, and between servers and cloud computing centers to 10Gbps. About 2,000 smart devices are installed inside the mall. The hospital's internal equipment is relatively complex, involving equipment monitoring, real-time diagnosis, and other tasks, simulating 40 EC nodes. In the energy consumption modeling process, the study comprehensively considers the hardware heterogeneity among edge nodes. The node computing power, energy consumption characteristics, and transmission bandwidth are modeled as input parameters, respectively. Node heterogeneity directly affects task offloading and resource allocation decisions. That is, low-computing-capacity or high-energy-consumption nodes are inclined to be assigned with lighter or latency-tolerant tasks during the optimization process. This further optimizes the energy consumption distribution and resource utilization while ensuring the overall system performance. The completion rate of resource allocation tasks for four types of models in different scenarios is shown in Figure 9.

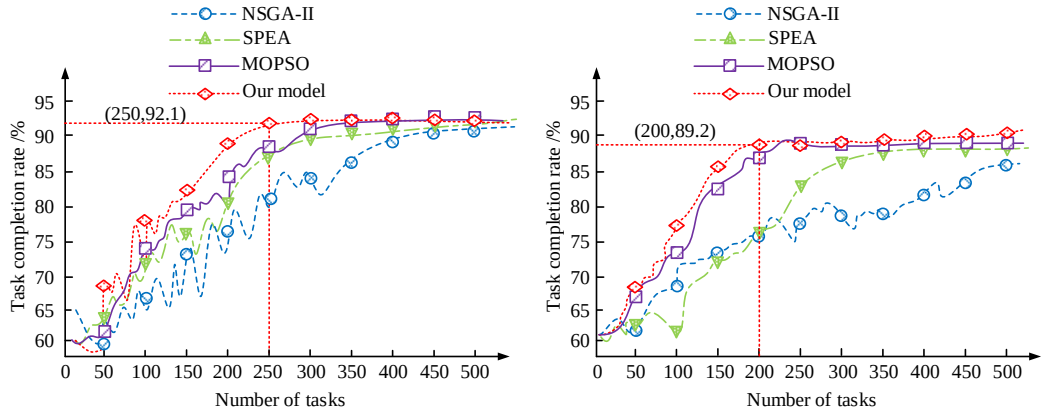


Figure 9: Success test of model resource allocation in shopping mall and hospital scenarios.

Figure 9 (a) shows the task completion rate results of four types of models in the shopping mall scenario. Figure 9 (b) displays the task completion rate results of four types of models in the hospital scenario. According

to Figure 9 (a), the task completion rate of the proposed model is significantly better than the other three models, reaching 92.1%, while the task completion rates of NSGA-II, SPEA, and MOPSO are 88.42%, 87.15%, and 90.34%, respectively. This result indicates that in the shopping mall scenario, the proposed model can better meet the real-time and processing requirements of the task, maximizing the task completion rate. From Figure 9 (b), the task completion rate of the proposed model is 89.2%, which is far higher than the other three models. It is proved again that the new model can better adapt to complex equipment monitoring and real-time diagnosis tasks in the hospital scene, and optimize the allocation of EC resources. During the resource allocation process, the model sets feasibility filtering criteria based on the memory capacity, processing capability, and bandwidth constraints of edge nodes. It allocates tasks only when the node resource constraints are met, ensuring the feasibility of the allocation scheme and the stability of the system. The MOPSO with better performance is selected and compared it with the proposed method. Taking the network load and delay as indicators, the results are shown in Figure 10. In this case, the network load is measured by recording the data transfer rate (in Mbps) between nodes in real-time, and the latency is calculated by recording the end-to-end delay (in ms) from the initiation of the task to the reception of the returned result.

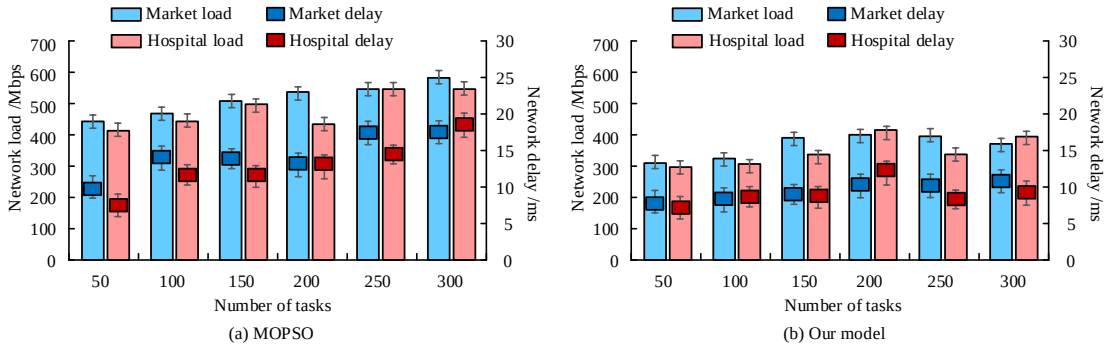


Figure 10: Load and delay comparison results of MOPSO and the designed method.

Figure 10 (a) shows the load and delay test results of shopping malls and hospitals in the MOPSO model. Figure 10 (b) shows the load and delay test results of shopping malls and hospitals in the proposed model. In Figure 10 (a), in the shopping mall scenario, with the increase of network tasks, the network load of MOPSO reached up to 600 Mbps. This indicated that the resource scheduling efficiency of the model was low under high user density, resulting in heavy network load. Meanwhile, the delay also significantly increased with the increase of network load, reaching a maximum of 18.4 ms. In the hospital scenario, although the network load was always lower than in the shopping mall scenario, the delay fluctuated between 10 ms and 15 ms, indicating higher user density and task quantity. From Figure 10 (b), the proposed model had significantly lower network loads in shopping malls and hospitals compared to MOPSO when handling multitasking, with average loads of 318 Mbps and average delays of 9.1 ms, respectively. This demonstrated that the proposed method could effectively control network load and delay in high load environments, with better resource allocation capabilities and optimization effects. Finally, the study conducted tests using resource utilization rate, allocation execution time, and total system energy consumption as indicators, as displayed in Table 3.

Table 3: Index test results of different models in shopping mall and hospital scenarios

Environment	Model	Resource utilization/%	Allocation execution time/s	Total system energy consumption/J
Mall	NSGA-II	75.34	15.87	230.57
	SPEA	72.18	16.5	240.63
	MOPSO	80.21	14.32	225.11
	Our model	83.49	12.94	215.32
Hospital	NSGA-II	68.92	18.25	280.47
	SPEA	70.14	17.88	290.25
	MOPSO	78.11	16.17	270.83
	Our model	81.67	14.68	260.02

According to Table 3, the proposed model in shopping mall and hospital scenarios was superior to other comparative models. In the shopping mall scenario, the resource utilization rate of the proposed model was 83.49%, the allocation execution time was 12.94 seconds, and the total energy consumption was 215.32 J. In the hospital scenario, the resource utilization rate was 81.67%, the allocation execution time was 14.68 seconds, and the total energy consumption was 260.02 J. Compared with NSGA-II, SPEA, and MOPSO models, the proposed model showed the highest resource utilization, the shortest allocation execution time, and the lowest system energy consumption in these two scenarios. This verifies its optimization effect in EC resource allocation, which can more effectively balance performance and energy efficiency, and improve the overall system performance. In addition, the results in Table 2 were based on the simulation experiments of EdgeDroid with CICIDS 2017 dataset. The statistics were the average values of system energy consumption under different dataset tests. On the other hand, the results in Table 3 were from tests conducted in actual application scenarios (shopping centers and hospitals), reflecting the average system energy consumption measured in specific deployment environments, hence there were differences in values. The study continued to validate the task offloading success rate, computational complexity, and task re-scheduling rate of the different approaches under different task priority fluctuation ranges. The results are shown in Table 4.

Table 4: Model performance results under fluctuating task priorities

Fluctuation level	Method	Task offloading success rate (%)	Computational complexity (ms)	Task rescheduling rate (%)
Small fluctuation (±1 level)	NSGA-II	90.7	240	11.2
	SPEA	89.3	235	12.5
	MOPSO	91.5	220	10.1
	Our model	95.8	185	6.3
Large fluctuation (±3 levels)	NSGA-II	86.4	255	18.9
	SPEA	84.9	250	20.3
	MOPSO	87.8	235	16.2
	Our model	92.4	190	10.5

From Table 4, under the condition of small priority fluctuation, the proposed model outperforms NSGA-II, SPEA, and MOPSO in task offloading success rate (95.8%), computational complexity (185 ms), and task re-scheduling rate (6.3%), and exhibits higher scheduling efficiency and stability. Under the condition of large priority fluctuation, although the overall performance of each method decreases, the proposed model still maintains the highest task offloading success rate (92.4%) and the lowest task re-scheduling rate (10.5%). The computational complexity grows less, which further verifies the adaptability and robustness of the proposed method under dynamic task priority change scenarios. Compared with traditional GA, the proposed IGA effectively improves global search capability and dynamic scheduling flexibility by introducing knowledge guided crossover and splitting variants, while increasing a small amount of computational overhead. This has good scalability for multi node heterogeneous device environments in large MEC systems. The optimization model can dynamically adjust resource allocation based on node algorithm power, prioritize low complexity tasks to low-power devices, and achieve overall energy efficiency optimization.

4 Discussion

Aiming at the problem of resource allocation efficiency and energy consumption optimization in EC environment, this paper proposed an IGA model incorporating knowledge-guided crossover and segmentation variants. The proposed model was comprehensively validated in the EdgeDroid and CICIDS 2017 datasets, as well as in real-world application scenarios in shopping malls and hospitals. The experimental results showed that the proposed model outperformed mainstream multi-objective optimization methods such as NSGA-II, SPEA, and MOPSO in terms of computational resource occupancy (minimum 77.45%), average energy consumption of the device (minimum 112.68J), and task processing time (minimum 5.44s) (p<0.05). The improvement in this performance was mainly due to the collaborative mechanism of knowledge-guided intersection. In the early stage, global search was accelerated, and in the later stage, variant segmentation was accelerated, enhancing population diversity. This effectively avoided the local optimization

problems that traditional GA is prone to. By dynamically balancing energy consumption, latency, and resource utilization targets through the resource aware fitness function, the overall flexibility and robustness of scheduling were enhanced.

Compared with NSGA-II's lack of efficiency in Pareto frontier exploration, SPEA's slow convergence of energy consumption under high load conditions, and MOPSO's large fluctuation of task completion rate, the proposed IGA was able to maintain a higher level of task success and energy efficiency under different task priority changes and server dynamics. This result verified its adaptive advantages in dynamic MEC environments. However, there are still some limitations to this study. The main reason is that IGA introduces additional cross and variance computation overhead in complex scenarios, which may lead to an overall increase in scheduling latency for large-scale node systems (such as thousands of edge nodes), although the time cost increase for a single iteration is small (about 8.5%). Moreover, although the current model has taken node heterogeneity into account, it has not yet been optimized for the extreme resource-limited devices. In addition, although the current model has considered node heterogeneity, there is still room for further optimization for the migration and deployment of extreme resource-constrained devices. Future work can combine the lightweight evolution strategy with the layered parallelism mechanism to further improve the scalability and real-time response capability of the algorithm in the ultra-large-scale distributed MEC environment.

5 Conclusion

To solve the optimization problem of MEC resource allocation in EC environment, the study constructed a multi-objective optimization function and improved the crossover and variance structure of the GA. A new EC resource allocation strategy model was proposed. The results showed that the training Loss reached a minimum of about 0.012 when the fitness adjustment factor was 0.8 and the cross-variance weighting factor was 0.75. The number of optimal solutions generated by the IGA that incorporated the knowledge crossover and segmentation variance was improved to nearly 4.8 in this setting. This was significantly optimized compared to both the traditional GA and the single-improved strategy. Compared with NSGA-II, SPEA, and MOPSO methods, the proposed model achieved the optimum in key metrics such as computational resource occupancy (minimum 77.45%), average energy consumption of the device (112.68 J), average energy consumption of the system (208.12 J), and average processing time (5.44 s). The task completion rates for the shopping mall and hospital scenarios were 92.1% and 89.2%, respectively. The average network latency was 9.1ms, the resource utilization rate was 83.49%, and the allocated execution time was 12.94s. It had scheduling advantages in dynamic multi-scenario environments. Nevertheless, considering the challenge of highly dynamic changes of edge nodes, dynamic scheduling methods based on real-time reinforcement learning can be explored in the future. Additionally, IGA can be fused with other evolutionary algorithms to further improve the model's real-time responsiveness and self-adaptive optimization in ultra-large-scale MEC systems.

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A Modeling-Driven Threat Analysis and Risk Assessment for Software-Defined Network Architecture

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In recent years, the networking field has been marked by the emergence of a new technology that seems set to revolutionize everything in our infrastructure. Software-Defined Networks (SDN), which present a new approach to networking with a different architectural philosophy. These changes in network infrastructure simplify equipment and make it independent. SDN is not a single solution or product, but rather a collection of innovative technologies that enable centralized control of network resources, improved programmability and orchestration of these resources, and virtualization by decoupling them from the physical elements of the network. However, increasing centralization raises serious security and privacy concerns, exposing networks to vulnerabilities including unauthorized access, data breaches, and malware infections. This article examines security concerns in the deployment of SDN in a campus network environment using a structured Threat Modeling approach based on the STRIDE methodology. Following a methodical methodology, we describe the SDN use case and illustrate its architecture using a Data Flow Diagram (DFD) to identify essential assets and communication flows in each zone of the SDN architecture. We then examine potential hazards to each zone, assess the risks, and recommend appropriate mitigation strategies. Our method is to improve the security and dependability of SDN, a technology that provides substantial benefits in terms of flexibility, scalability, and network management but is vulnerable to a variety of cyber threats if not properly guarded. The combination of STRIDE threat modeling and CVSS scoring enables a comprehensive understanding of vulnerabilities in SDN environments, prioritizing mitigation efforts based on exploitability and impact. Specific outcomes include T11, rated as a Critical risk with a CVSS score of 9.8, and T5 and T4 reaching Extreme levels in the 5x5 matrix. This approach helps to address high-risk threats while ensuring a balanced security strategy across varying threat levels.

Povzetek: Opisano je ogrodje za modeliranje groženj in oceno tveganja v SDN-omrežjih z uporabo STRIDE, CVSS 3.1 in 5×5 matrike za celovito, podatkovno podprto varnostno strategijo.

1 Introduction

Software-Defined Network (SDN) represents a major advancement in network management and configuration. Unlike traditional network architectures, where controllers and switching devices are tightly integrated, SDN separates the control plane from the data plane [1]. The data plane consists of network devices such as switches, while flow management and decision-making are handled by the controller, which is the brain of the network. This controller, the smartest part of the network, makes decisions and manages traffic, including packet dropping. This separation enables centralized and scheduled network management, providing increased flexibility to adjust policies and configurations in real time [2].

However, despite its many benefits, SDN system introduces significant security challenges. SDN networks are inherently vulnerable to various threats due to their centralized control plane, the communication between controllers and network elements, and their reliance on programmable interfaces. Attackers can exploit these vulnerabilities to manipulate network traffic, launch Denial-of-Service (DoS) attacks, or gain unauthorized access to critical infrastructure [3]. Ensuring the security, integrity, and confidentiality of SDN networks is therefore a major concern. Moreover, traditional security mechanisms designed for conventional networks are often inadequate for SDN environments. The separation of the control and data planes, along with the open nature of SDN protocols such as OpenFlow, creates new attack vectors that require specialized security approaches [4].

Threat modeling is a crucial methodology for proactively identifying and mitigating security risks in

SDN networks. By systematically analyzing the components, data flows, and potential attack vectors, threat modeling helps security professionals anticipate threats and implement appropriate countermeasures [5].

In this paper, we propose a structured approach to threat modeling in SDN environments. This paper proposes a structured threat identification and risk quantification framework for SDN based on STRIDE, CVSS 3.1 scoring, and a 5×5 risk matrix to guide mitigation strategy selection. Our methodology consists of several steps, namely: defining the SDN-based network infrastructure and identifying vulnerabilities, generating data flow and process flow diagrams, identifying threats, and applying risk assessment to evaluate their impact on confidentiality, integrity, availability, and other security objectives if the identified vulnerabilities are exploited. The threats are then categorized, and corresponding mitigation strategies are proposed. The structure of this paper is as follows: Section 2 provides an overview of SDN and its vulnerabilities. Section 3 discusses the threat modeling methodology and tools. Section 4 presents the proposed methodology. Section 5 details the results along with a discussion. Finally, conclusions are drawn in Section 6.

2 Related work

Table 1 presents a comparative analysis of recent works on SDN security, highlighting the threat models used, SDN layers analyzed, evaluation metrics, and the overall scope of each study. This comparison underscores the novelty and completeness of our approach in addressing both qualitative and quantitative aspects of SDN threat assessment

Given the importance, topicality, and richness of the subject, it has been the subject of various researches and articles, and has been tackled from different nails and approaches. The study in [6] presented a security evaluation framework for SDN architectures in data center environments. It uses STRIDE and PASTA models to identify threats and vulnerabilities across all SDN layers. The framework includes CVSS-based risk assessment, attack modeling in a Mininet-ONOS testbed, and mitigation strategies using specific and centralized countermeasures.

Authors in [7] conducted a Systematic Mapping Study (SMS) to investigate how SDN controllers enhance security in IoT networks. It analyzes 33 studies, focusing on types of SDN controller architectures, security issues, and mitigation techniques. The study finds centralized controllers most used but highlights their limitations. It also identifies gaps and future research directions in securing SDN-IoT environments.

The research in [8] proposed a comprehensive threat model for SDN by identifying four key use cases where security breaches can occur: applications attacking controllers, inter-controller attacks, controllers attacking switches, and switches attacking controllers. It analyzed each scenario, compared them with traditional networks, and provided tailored countermeasures.

The work in [9] presented a model-based method for simulating and analyzing threats in in-vehicle networks, focusing on modern vehicles increasingly integrating IoT and SDN technologies. The approach involved capturing network data, creating a data model in DBC format, synthesizing a functional model using SysML, and translating it into a detailed simulation model. The method included steps for model validation and threat analysis by simulating various attack types such as DoS, frame injection, and fuzzing.

The authors in [10] introduced a systematic framework for modeling and analyzing the security of SDN systems. The authors proposed a novel graphical security model called Threat Vector - Hierarchical Attack Representation Model (TV-HARM), which captured complex attack paths and threat combinations in SDN environments. To assess the security posture, the framework employed three types of metrics: Network Centrality Measures, Vulnerability Scores and Attack Impact Metrics.

This present article provides a modeling-driven threat analysis and risk assessment framework tailored for SDN architectures. Compared to existing literature, this paper offers a more comprehensive and actionable approach to securing SDN architectures. While prior works have typically focused on threat identification using models such as STRIDE or custom use-case scenarios, they often fall short in translating these threats into quantifiable risk levels. This paper bridges that gap by integrating STRIDE for systematic threat modeling, CVSS for standardized quantitative risk scoring, and a 5×5 risk matrix for intuitive risk visualization and prioritization. The approach enables comprehensive analysis across the SDN application, control, and data planes, supporting informed decision-making for securing SDN deployments.

3 Background

In this section, we present the architecture of software-defined networks and their components, followed by a discussion of the security challenges associated with this architecture.

3.1 SDN architecture

The SDN architecture is composed of several layers and interfaces, as illustrated in Figure 1 [11], [12].

Table 1: Comparative analysis of existing works on SDN security

Reference	Model Used	SDN Layer Analyzed	Metrics Employed	Scope
Ivkić et al. [6]	STRIDE, PASTA	All SDN Layers	Threat mapping, risk classification	Data Center SDN
Oredola & Ashraf [7]	Systematic Mapping Study (SMS)	Control Plane	ML performance metrics (Precision, Recall), Packet Analysis	SDN-IoT
Sharma & Tyagi [8]	Custom Use-Case-Based Threat Model	All SDN layers	Comparative analysis, attack taxonomy	SDN architecture
Lekidis et al. [9]	Stochastic Model Checking with CTMCs (PRISM tool)	Control and Application	Reaction time, Network cost, Attack success probability	SDN controller
Eom et al. [10]	TV-HARM (Threat Vector-Hierarchical Attack Representation Model)	Control and Data Network	Centrality Measures, Vulnerability Scores, Attack Impact Metrics	SDN environments

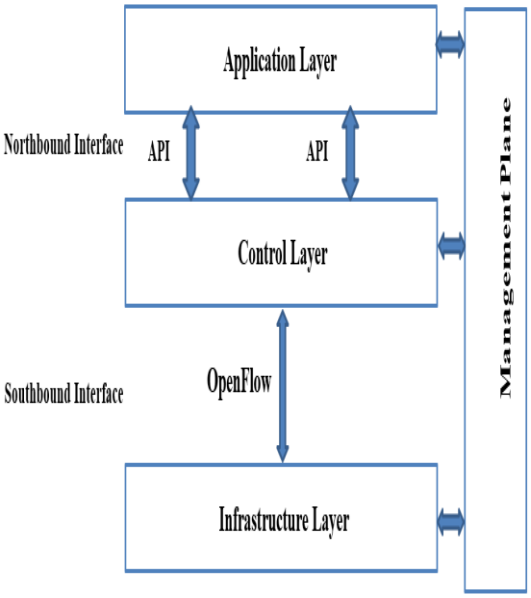


Figure 1: Architecture of SDN network

- **Infrastructure layer**

The infrastructure layer is made up of interconnected network pieces. Data links enable interconnection inside the infrastructure. Each connection connects a port on one network device to another's port. A network element computes, stores, and forwards network traffic. Network parts include virtual or hardware switches, routers, middle boxes, and other network components. They feature open programmable interfaces. The control layer uses these interfaces to reprogram their behavior and retrieve their local states. They deal directly with network traffic, performing forwarding, routing, caching, packet inspection, and other networking functions.

- **Southbound API**

The southbound API provides an open, customizable interface between the infrastructure and control layers. It facilitates interactions between the two layers by providing all required abstractions and protocols. It has two primary roles. It gives the control layer abstractions for interacting with network elements. Furthermore, it executes control layer directives on network elements. This standardized, open interface enables the control layer to reprogram the infrastructure layer's forwarding behavior and determine its status. The access plane layer is typically configured using flow rules. Flow rules consist of a set of matching fields linked with actions, as well as instructions indicating how the network element should carry out these actions. Flow rules are stored in OpenFlow tables on the network elements.

- **Control layer**

The control layer is considered the network's brain. It is a conceptually centralized entity that uses interfaces, network operations, network status, and a development environment to govern network element behavior. It abstracts network infrastructure, analyzes network status, and generates network knowledge. Network programs employ these abstractions to reprogram network components. Furthermore, SDN controllers transform application policies into low-level rules. They verify that the rules installed in network elements are consistent and valid. They also monitor network elements and traffic by collecting network status, network events, metrics, and other information.

- **Northbound API**

The northbound API provides a configurable interface between network controllers and applications. It enables the latter to communicate with the control plane and distribute its requirements throughout the network architecture. This abstraction enables network applications to fully leverage SDN capabilities such as global awareness, programmability, automation, and policy deployment. It provides network applications with universal data models, network states, management information, and other capabilities. These programs use the interface to change the behavior of network nodes and update the network state.

- **Application layer**

The application layer is located at the top of the SDN architecture. It includes the network applications. It abstracts the business logic, requirements, and goals of network stakeholders. This layer frequently communicates with third-party apps, administrators, developers, and other stakeholders. It converts these interactions into network policies and tactics. It then delivers them to the control layer via the northbound interface in order to configure or gather status of the network infrastructure.

- **Management layer**

The management layer coordinates the configuration and orchestration of software and hardware resources across the other SDN layers. It also communicates with administrators, allowing them to control and monitor SDN layers. The Manager looks after the SDN software and hardware resources. It delivers them in the right hardware and configurations. It modifies them based on network traffic and business logic. It manages their entire lifecycle. It tracks the use, operation, and quality of SDN resources. It gathers domain knowledge from every controller. It combines this knowledge with monitoring data to create a complete picture of the network.

3.2 Vulnerabilities in SDN

SDN offer numerous advantages over traditional networks. The separation of the control and data transport layers, as well as the centralization of network control in an SDN controller, enables more efficient and consistent network management. Thanks to their programmability, SDN networks allow administrators to dynamically define and adjust network policies, facilitating the automation of network functions and reducing operating costs [13].

Furthermore, the increased flexibility of SDN networks enables faster response to changing network and application needs, accelerating time to market for new applications. Improved responsiveness to problems and outages also contributes to higher network availability. SDN optimizes performance by directing traffic more efficiently and avoiding bottlenecks (Figure 2).

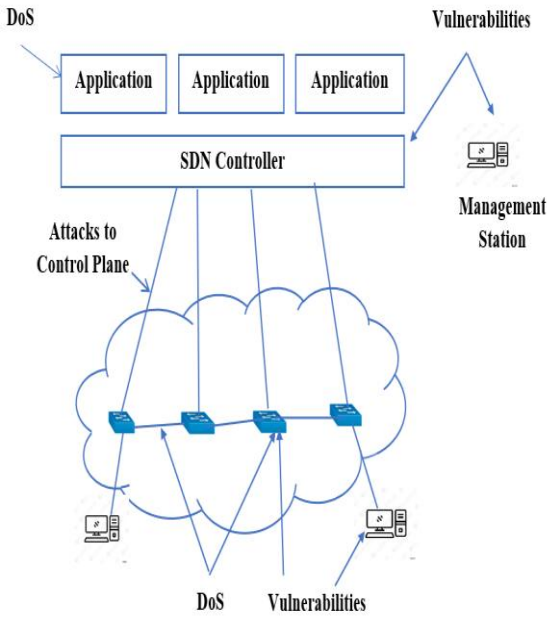


Figure 2: Vulnerabilities in SDN architecture

- **Between the network device and the host**

There are various ways to maliciously exploit network devices in the SDN data plane. A malicious host can attack any SDN switch or controller by generating forged network packets.

- **On the network device**

In SDN networks, the controller installs flow rules in a switch's flow tables, either proactively or reactively. However, switches have a limited number of flow table entries, posing a challenge in managing flow rules efficiently. Since SDN separates the control plane from the data plane, a critical security issue for OpenFlow switches is differentiating between legitimate and malicious flow rules. Additionally, the number of flow entries a switch can handle is a limiting factor. OpenFlow switches must buffer data flows while awaiting flow rules from the controller, making them vulnerable to flooding attacks. Due to resource constraints, an OpenFlow switch can struggle to buffer large volumes of unwanted UDP or TCP traffic, increasing its susceptibility to such attacks.

- **Between network devices**

SDN switch link communications are not encrypted, creating a vulnerability that enables attackers to intercept transmitted data, compromising network security.

- **Between controller and network device**

In SDN, if a switch fails to receive flow routing instructions from the controller—whether due to a controller failure or disconnection—the data plane becomes inoperable. This makes the link between the switch and the controller a prime target for attackers, necessitating strong security measures. Additionally, OpenFlow 1.3 does not natively encrypt communications between the controller and network devices using SSL or

TLS, nor does it enforce controller-level switch authentication. This lack of encryption and authentication exposes the entire SDN network to security threats, including unauthorized data access, man-in-the-middle attacks, eavesdropping, and manipulation of flow rules [14].

- **Between controllers**

Links between SDN controllers are exposed to various security threats. To ensure redundancy, controllers exchange update information; however, the absence of encryption on these links allows attackers to intercept and manipulate critical updates, compromising network integrity and security.

- **On the controller**

SDN threats arise from the separation of the control and data planes, as well as the reliance on a logically centralized controller. As the core component responsible for network control, the SDN controller is a prime target for attacks. Applications running on top of the controller can introduce security risks if not properly managed. To mitigate these risks, the controller must implement strong authentication and authorization mechanisms for applications, ensuring they are segregated based on their security impact before accessing network information. Additionally, a compromised workstation within the same network as the SDN controller can facilitate direct attacks, potentially leading to full network compromise. Furthermore, attackers can exploit the controller's ability to interpret and enforce network policies to orchestrate large-scale attacks. Given its central role in managing traffic, the SDN controller can also become a performance bottleneck, further impacting network resilience [15].

- **Between applications and the controller**

Unlike the standardized Southbound API, the Northbound API lacks a universal standard and has inherent security weaknesses. The absence of robust trust mechanisms in the Northbound API, which facilitates communication between applications and the controller, introduces potential vulnerabilities. Weak authentication methods and inadequate authorization controls can enable attackers to impersonate legitimate applications or gain unauthorized access, posing a significant security risk [16].

- **On the application**

Attackers often exploit applications to gain control over an SDN controller, a risk amplified by the fact that both applications and controller software are typically hosted on the same physical system. This allows malicious code to be injected into the control software through the Northbound API, which remains a vulnerable point of entry. The combination of untrusted applications and inherent API weaknesses enables an attacker to compromise the controller, ultimately allowing them to manipulate network rules and take control of the entire SDN infrastructure.

4 Threat modeling

Recent high-profile security breaches have demonstrated that reactive security solutions are inadequate. Proper threat modeling could have avoided some of these incidents [17],[18]. Various threat modeling tools are available, including DREAD, PASTA, OWASP Threat Dragon, and STRIDE [19].

- **DREAD**

The DREAD threat model is a risk assessment system that enables businesses to measure, compare, and prioritize the risk of security threats. The term DREAD stands for Damage, Reproducibility, Usability, Affected Users, and Discoverability. Each component contributes to a thorough assessment of potential security vulnerabilities, allowing teams to determine informed resource allocation and mitigation measures. DREAD, which was initially established as part of Microsoft's Security Development Lifecycle (SDL), has since become a widely adopted approach across a variety of sectors. Although Microsoft has since embraced alternative threat modeling methodologies, DREAD remains relevant due to its simplicity and practical application in a wide range of settings.

- **PASTA**

The PASTA abbreviation stands for Process for Attack Simulation and Threat Analysis. PASTA is a seven-step threat modeling methodology that integrates business objectives and technical requirements to deliver a comprehensive risk assessment of potential threats. Unlike other threat modeling methodologies, which may focus solely on technical vulnerabilities, PASTA adopts a comprehensive approach that considers both business effect and technological concerns. This comprehensive approach makes it especially effective in company situations where security decisions must be consistent with business objectives. The PASTA methodology is iterative and flexible, allowing organizations to tailor it to their own requirements while retaining a structured approach to threat assessment. By emphasizing risk-based analysis, PASTA assists organizations in prioritizing security investments and focusing on protecting their most valuable assets.

- **OWASP Threat Dragon**

OWASP Threat Dragon is a threat modeling tool designed to create threat model diagrams within the secure development lifecycle. Aligned with the principles of the Threat Modeling Manifesto, it helps document potential threats, define mitigation strategies, and visually represent threat model components and attack surfaces. Available as both an online and desktop application, Threat Dragon facilitates comprehensive threat analysis and security planning.

- **STRIDE**

STRIDE stands for Spoofing, Tampering, Repudiation, Information Disclosure, Denial of Service and Elevation of Privilege. STRIDE is commonly used in

cybersecurity to analyze potential security risks in applications, networks, and systems [20].

Each strategy aims at a specific perspective and will be more relevant and effective in some contexts than others; this paper will focus on STRIDE as a methodology. Microsoft developed the STRIDE threat model, which has emerged as one of the most effective models for proactive security planning. The STRIDE is a systematic approach to security that encourages development teams to think like hackers in order to defend their systems before they are breached [21]. Unlike DREAD, which primarily focuses on scoring and prioritizing threats based on impact and exploitability without offering a systematic method for discovering them, STRIDE enables a comprehensive mapping of threats to specific elements within the SDN system. While PASTA offers an attacker-centric and risk-driven methodology suitable for enterprise-level threat modeling, it requires extensive contextual and business-driven inputs, which can be complex and less adaptable in SDN infrastructure scenarios. Similarly, OWASP Threat Dragon, although user-friendly and valuable for visual modeling, is primarily a tool rather than a full framework, and it often depends on the underlying threat model being applied—such as STRIDE itself. Therefore, STRIDE was chosen for its clarity, ease of integration with data flow diagrams, and its alignment with technical threat categorization, making it particularly effective for identifying and structuring threats in programmable, software-driven networks like SDN. The STRIDE model divides threats into six categories, each addressing a different component of software security risk (Table 2).

Table 2: STRIDE model threat and security objective violation

Threat	Security objective violation
Spoofing	Authentication
Tampering	Integrity
Repudiation	Non-repudiation
Information disclosure	Confidentiality
Denial of Service	Availability
Elevation of privilege	Authorization

Spoofing: Consider digital identity theft. This entails mimicking another user or system component in order to obtain illegal access. Spoofing attacks exploit authentication methods, allowing hackers to impersonate genuine users or devices.

Tampering: Tampering refers to the unlawful modification of data or code. Such assaults might jeopardize data integrity by modifying files, databases, software code, deployment pipelines, or memory in live systems. Tampering with any system carries significant hazards, particularly when data accuracy is crucial for decision-making.

Repudiation: Threats of repudiation take advantage of accountability gaps. This type of security danger happens when a user or system refuses to complete a certain task, such as a transaction. This threat takes advantage of a lack of non-repudiation measures in software systems, making it harder to hold parties accountable for their behavior.

Information disclosure: This is the unintended disclosure of confidential or sensitive information to unauthorized people. This could be due to insufficient encryption, inappropriate access controls, or vulnerabilities in web applications.

Denial of Service: This type of security threat attempts to disrupt service availability by overloading the system with excessive requests or exploiting system weaknesses. DoS attacks make systems unavailable to legitimate users and disrupt company operations.

Elevation of privilege: This happens when a hacker gains unauthorized access, typically by exploiting a system vulnerability. This can result in administrative control over a system, allowing the attacker to install malware, change system settings, or view sensitive data.

5 Proposed methodology

In this section, we introduce the steps of our proposed methodology, including the DFD diagram, threat identification, risk assessment, and threat mitigation.

5.1 Data flow diagram

A graphical representation of the SDN architecture is called a Data Flow Diagram (DFD). Understanding the sequence of information exchanges and, more importantly, identifying the vulnerabilities and threats associated with the architecture's assets is made easier by simplifying the processes using the DFD. This aids in proposing a mitigation and correction plan that may involve reducing, eliminating, or avoiding the threat altogether to better manage its potential impact if exploited [22]. To construct and analyze the DFD, we used the Microsoft Threat Modeling tool (MTM) with Azure Threat Modeling Tool (ATMT) version 1.0.0.33, which is a security design analysis tool developed by Microsoft. It supports STRIDE-based threat identification by automatically generating potential threats based on defined elements such as processes, data stores, data flows, and external entities. This process aids in proposing a mitigation and correction plan that may involve reducing or eliminating the threat entirely or avoiding it to better manage the potential impact in the event that it is exploited.

In Figure 3, rectangular shapes with solid black borders represent key network components, such as user hosts, SDN infrastructure devices (e.g., switches and host devices), and software entities. The circular shape

represents the orchestration and management application, which serves as an intermediary layer for communication between the user's host and the SDN controller. Green rounded rectangles indicate the flow of communication between components, distinguishing requests and responses. The red dotted box outlines the Network Domain, which includes essential SDN data plane elements such as the switch and host device. These components interact directly under the supervision of the SDN controller, which resides outside the network domain, representing the centralized control plane. Starting from the top left, the human user interacts with the user's host, which then communicates with the orchestration and management application. This application forwards requests to the SDN controller, which then controls and manages the data flow to the switch and host device within the network domain. This layout visually represents the logical separation between the application, control, and data planes, central to the SDN architecture.

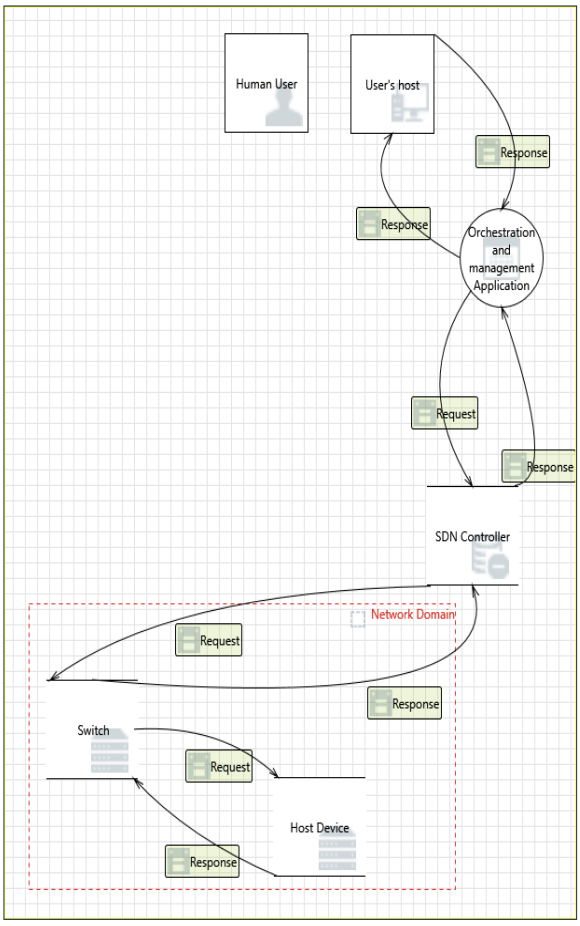


Figure 3: Data flow diagram of SDN network using Microsoft Threat Modeling tool

5.2 Threat identification

Threat identification comes next once the threat modeling approach is used, as seen in Figure 3.

A thorough threat report was produced for every DFD component by using the MTM tool's STRIDE threat modeling technique. All of the dangers that were found were then individually recorded in sub-section 5.1 of the findings. These risks illustrate how different threats can compromise particular components. Additionally, we described the SDN assets affected by each STRIDE threat and how they relate to violations of security requirements. We also examined which threats could result in attacks after classifying all of the threats found in each SDN zones using the STRIDE approach.

5.3 Risk assessment

A crucial part of threat modeling is risk assessment, which helps organizations efficiently prioritize and address possible risks. Threat modeling is an organized method for enhancing system security by methodically identifying and evaluating hazards [23]. The CVSS and the 5x5 risk matrix are two popular techniques for measuring and visualizing risks. A standardized framework for assessing vulnerability severity based on variables including effect, exploitability, and environmental changes is offered by CVSS. In addition, the 5x5 matrix provides a simple and easy-to-use tool for decision-making by visualizing risks by classifying them based on likelihood and impact. By combining these techniques, security teams may strike a compromise between practical prioritization and quantitative accuracy, guaranteeing that mitigation efforts concentrate on the most serious risks [24]. This article explores how CVSS and the 5x5 matrix can be integrated, emphasizing how they work together to create a thorough framework for risk assessment.

5.4 Threat mitigation

Proposing suitable mitigation strategies comes after assessing risks and detecting threats in SDN network. Threat mitigation is the process of lowering or getting rid of possible hazards in a system. We examined a number of current methods in order to create effective mitigation measures. Based on these investigations, we chose the best solutions to safeguard the SDN network from these possible dangers, as covered in section 5.3.

6 Results and discussion

In this section, we detect threats and test the risk assessment using the STRIDE technique through experiments using the MTM tool. As was previously said, STRIDE uses the use case to map and classify the threats that have been identified. We applied the STRIDE threat modeling approach in our SDN architecture to systematically identify security vulnerabilities across the control, data, and application planes. Based on the findings, we proposed mitigation strategies to enhance the resilience of the SDN framework against potential attacks.

6.1 Threats identification

In this part, we discuss all the threats identified by STRIDE tool with respect to each zone of the SDN architecture (Table 3).

Table 3: Threat identification following STRIDE approach

SDN zones	STRIDE	Threats	Mapped DFD Element
SDN network element	Spoofing	**T1:** An attacker may spoof the Host Device, resulting in erroneous data being transmitted to the switch.	Host device
		T2: An attacker may impersonate Switch, causing data to be written to the attacker's target rather than Switch.	Switch Input
	Repudiation	**T3:** Switch states that it did not write data received from another entity over the trust boundary.	Data Handling
SDN controller	Spoofing	**T4:** An attacker may impersonate the SDN Controller, resulting in erroneous data being supplied to the attacker's target.	Controller Input
		T5: An attacker may impersonate the SDN Controller, resulting in false data being supplied to the orchestration and management applications.	Controller Data
		T6: An attacker may spoof the SDN Controller, causing data to be written to the attacker's target rather than the SDN Controller.	Controller Output
	Repudiation	**T7:** SDN Controller asserts that it did not write data received from another entity across the trust boundary.	Trust Boundary
	Information Disclosure	**T8:** Improper data protection on SDN Controllers can allow an attacker to view information that was not intended for dissemination.	Sensitive Data Flow
	Denial of Service	**T9:** An external agent restricts access to a data store on the other side of the trust boundary.	Data Store Access
		T10: An external agent disrupts data flow across a trust border in either direction.	Data Flow Disruption
SDN application	Spoofing	**T11:** An attacker may fake a user's host, resulting in unauthorized access to the Orchestration and Management Application.	User Access
	Tampering	**T12:** The web server 'Orchestration and Management Application' may be vulnerable to a cross-site scripting attack since it does not sanitize untrusted input.	Web Server Input
		T13: The web server 'Orchestration and Management Application' may be vulnerable to a persistent cross-site scripting attack since it does not sanitize data store 'SDN Controller' input and output.	Data Interaction
	Elevation of Privilege	**T14:** Orchestration and Management the application may be able to spoof the context of the user's host in order to gain further privileges.	User Context

6.2 Risk assessment

In order to preserve resources and assets, lower financial losses, enhance decision-making, and other goals, risk assessment entails evaluating the threats found through threat modeling, quantifying the risks, and implementing mitigation strategies.

- **CVSS calculator 3.1**

The Common Vulnerability Scoring System (CVSS), which assigns a risk score on a range of 0 to 10 in ascending order based on the severity and effect of the vulnerability, can be used to evaluate the risks associated with the threats and vulnerabilities mentioned above.

Table 4 presents how the score is divided according to the severity and the criticality hierarchy of the vulnerability.

Table 4: Allocation of vulnerability severity scores according to CVSS.

Severity	Score
None	0
Low	0.1 ➔ 3.9
Medium	4.0 ➔ 6.9
High	7.0 ➔ 8.9
Critical	9.0 ➔ 10.0

Following CVSS v3.1 calculator, the score is calculated by calling up the following parameters in Figure 4 and Table 5.

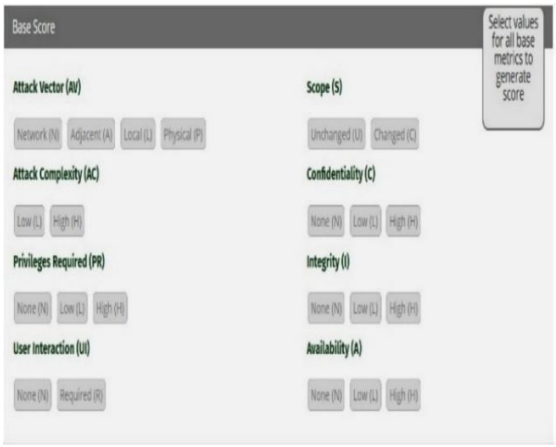


Figure 4: Common vulnerability scoring system version 3.1 calculator base score

- **AV (Attack Vector)**: N (Network), A (Adjacent), L (Local), P (Physical)
- **AC (Attack Complexity)**: L (Low), H (High)
- **PR (Privileges Required)**: N (None), L (Low), H (High)
- **UI (User Interaction)**: N (None), R (Required)
- **S (Scope)**: U (Unchanged), C (Changed)
- **C (Confidentiality Impact)**: N (None), L (Low), H (High)
- **I (Integrity Impact)**: N (None), L (Low), H (High)
- **A (Availability Impact)**: N (None), L (Low), H (High)

The bar chart in figure 5 illustrates the frequency and severity of CVSS-evaluated threats across different SDN architecture zones: Network Elements, Controller, and Applications.

Table 5: Risk management table (CVSS v3.1 base score)

Threat	AV	AC	PR	UI	S	C	I	A	Score	Severity
T1	N	L	N	N	U	L	L	N	6.5	Medium
T2	N	L	N	N	U	N	H	N	7.5	High
T3	N	H	L	N	U	N	L	N	3.1	Low
T4	N	L	N	N	U	H	N	N	7.5	High
T5	N	L	N	N	U	L	L	N	6.5	Medium
T6	N	L	N	N	U	N	H	N	7.5	High
T7	N	H	L	N	U	N	L	N	3.1	Low
T8	N	H	L	N	U	H	N	N	5.3	Medium
T9	N	L	N	N	U	N	N	H	7.5	High
T10	N	L	N	N	U	N	N	H	7.5	High
T11	N	L	N	N	U	H	H	H	9.8	Critical
T12	N	L	N	R	C	L	L	N	6.1	Medium
T13	N	L	N	R	C	L	L	N	6.1	Medium
T14	N	L	L	N	U	H	H	H	8.8	High

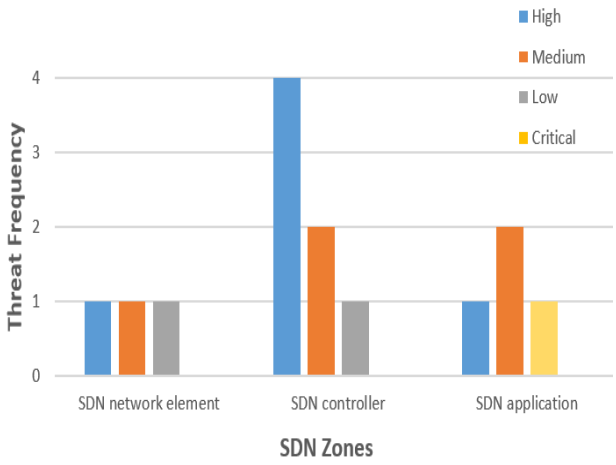


Figure 5: Frequency and severity of threats by SDN zones

The SDN Controller zone emerges as the most targeted, with several High severity threats, including spoofing and DoS attacks (T4–T10). The Application zone, though having fewer threats overall, contains the most severe one (T11 - Critical), involving user impersonation. Interestingly, while the Network Element zone hosts fewer threats, it includes Medium and High severities, suggesting vulnerabilities in identity verification mechanisms. The chart underscores the SDN Controller's critical role in the network and the need to harden it against identity- and access-based threats. The Application zone also requires attention, particularly regarding secure development practices to avoid injection-based vulnerabilities.

The severity distribution histogram across STRIDE categories reveals that Spoofing and DoS are the most critical threat categories in the SDN architecture, with Spoofing showing the highest frequency and including multiple High and Critical severity threats, indicating significant risks related to identity impersonation and unauthorized access. DoS threats also rank high in severity, highlighting vulnerabilities in system availability and resilience. In contrast, other categories such as Repudiation, Information Disclosure, Tampering, and Elevation of Privilege appear less frequent and mostly of Low to Medium severity, suggesting they are comparatively less impactful in the analyzed context. This distribution underscores the need to prioritize robust authentication, controller validation, and availability safeguards in SDN security strategies (Figure 6).

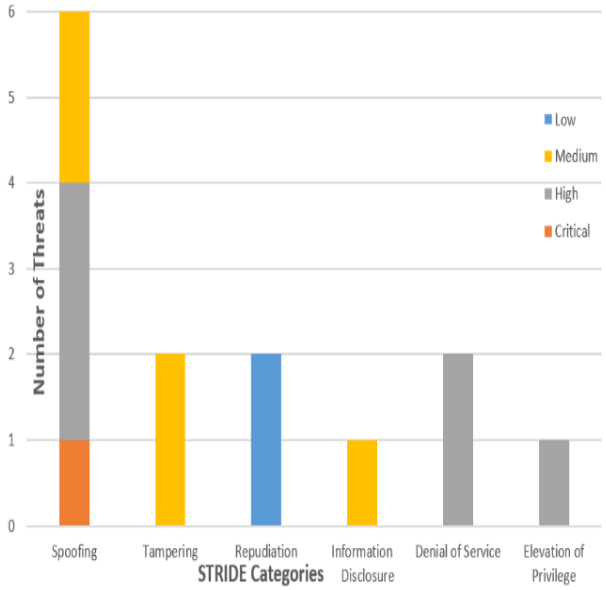


Figure 6: Severity distribution across the STRIDE categories

- **5 by 5 Matrix**

Prior to undertaking the evaluation, assets should be identified and prioritized using the 5 by 5 Risk Matrix, a helpful tool for risk assessment that combines threat impact and likelihood ranked from low to extreme. The likelihood is the possibility that the risk will materialize, whereas the impact is the severity of the consequences if the risk materialized. According to the matrix in Figure 7, the risk is color-coded in green, yellow-low, orange, and red, and can be classified as low, medium, high, or extreme using the formula:

Risk rating = Impact * Likelihood

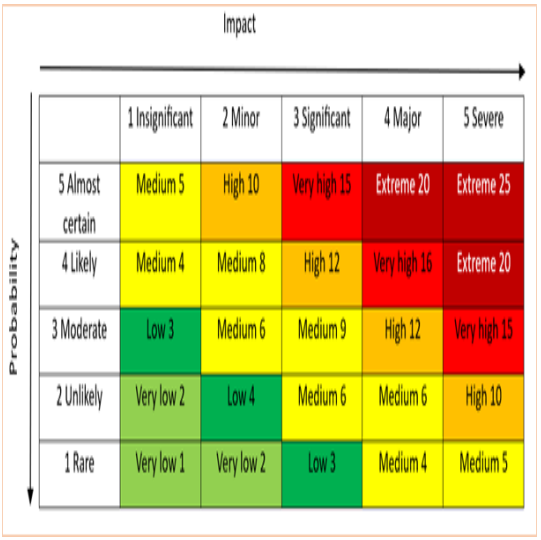


Figure 7: 5 by 5 risk matrix

Based on the 5x5 matrix, a threat assessment was carried out, and summarized in the table 6.

Table 6: Risk rating based on 5 by 5 risk matrix

Threat	Likelihood	Impact	Risk rating
T1	Likely (4)	Major (4)	Very High (16)
T2	Likely (4)	Severe (5)	Extreme (20)
T3	Moderate (3)	Minor (2)	Medium (6)
T4	Almost Certain (5)	Major (4)	Extreme (20)
T5	Almost Certain (5)	Severe (5)	Extreme (25)
T6	Likely (4)	Severe (5)	Extreme (20)
T7	Moderate (3)	Minor (2)	Medium (6)
T8	Likely (4)	Significant (3)	High (12)
T9	Unlikely (2)	Major (4)	Medium (6)
T10	Unlikely (2)	Major (4)	Medium (6)
T11	Almost Certain (5)	Major (4)	Extreme (20)
T12	Likely (4)	Significant (3)	High (12)
T13	Likely (4)	Significant (3)	High (12)
T14	Likely (4)	Severe (5)	Extreme (20)

Because the SDN system requires a high level of vigilance regarding data confidentiality, integrity, and availability—given the critical nature of the information circulating within the architecture and the potential consequences of compromise—any incorrect decision-making or unauthorized access could lead to severe network disruptions. As a result, the risk assessment of threats is often rated very high, whether using the CVSS framework or a 5x5 risk matrix, thereby increasing the overall risk level.

6.3 Threat mitigation techniques

It's time to provide a list of mitigation strategies to lessen the potential harm that could result from one of the threats being exploited after they have been recognized and categorized by zones using the STRIDE approach.

- **SDN network element**

Implement standard mutual authentication using CA-signed certificates or pre-shared keys to prevent spoofing of switches and other elements in both the control and data planes. Use secure boot and firmware validation to ensure the integrity of devices. Enable packet-level logging and auditing with timestamps and source identifiers to detect anomalies. To manage resource use, apply rate-limiting on packet-in messages from switches to the controller to prevent control plane flooding.

- **SDN controller**

Secure the SDN controller by enforcing TLS-based mutual authentication for all communication with switches and applications. Apply role-based access control (RBAC) to restrict administrative privileges and prevent unauthorized actions. Use encryption with secure key management for sensitive data exchanges and configuration files. Isolate critical modules and northbound applications using containerization or sandboxing techniques. Monitor for anomalies such as excessive flow table misses using Intrusion Detection Systems (IDS). Enforce timeout-based flushing of unused flow rules and resource caps per switch or application to mitigate denial-of-service (DoS) risks and preserve controller availability.

In terms of practical deployment, ONOS supports mitigations through its SecurityMode configuration for mutual TLS, Intent Framework for flow rule enforcement and application isolation, and the ability to implement rate-limiting via custom intents. Floodlight enables secure communication through mutual TLS, enforces flow rules, and implements RBAC for access control. It also supports API security and application isolation. OpenDaylight, with its AAA security plugin, provides RBAC, secure REST APIs, mutual TLS, and Karaf-based application isolation, offering a robust platform for enforcing security controls. Ryu, using OpenFlow TLS authentication, allows flow rule enforcement, rate-limiting, and secure RESTful API access, making it a versatile controller for securing SDN environments.

- **SDN application**

Strengthen application security by enforcing mutual authentication and message signing between applications and the controller. Implement strict API access policies to limit interaction only to authorized modules. Utilize application whitelisting and run-time monitoring to detect unexpected behavior. Use rate-limiting and resource quotas on northbound requests to prevent application-induced overload. Isolate applications using virtual machines or containers, and enforce code-signing and verification before deployment.

6.4 Discussion

The results from the STRIDE and CVSS 5x5 matrix highlight a range of threats across different SDN zones, with varying levels of risk severity. The CVSS scores provide a nuanced view of the potential impact and exploitability of each threat, allowing us to prioritize mitigations effectively. Threats such as T11, with a critical CVSS score of 9.8, point to vulnerabilities with a significant and broad impact on confidentiality, integrity, and availability, indicating an urgent need for countermeasures. Similarly, threats like T2, T4, and T6, with high severity scores (7.5), suggest vulnerabilities that could lead to severe data corruption or denial of service, requiring immediate attention but possibly with less widespread consequences than T11. On the other hand, threats such as T3 and T7, with low CVSS scores (3.1), may have limited consequences and are lower priority for remediation, yet they still need to be addressed as part of a comprehensive security strategy. The CVSS severity classification—ranging from Low to Critical—guides the prioritization of resources, ensuring that high-risk vulnerabilities are handled first. By combining both STRIDE threat modeling and CVSS scoring, organizations can better understand the threat landscape in SDN environments and make informed decisions about which vulnerabilities to address based on their exploitability, impact, and potential consequences.

7 Conclusion

This paper highlights the security threats that can compromise an SDN-based network architecture. Given the critical role of SDN in managing and optimizing modern network infrastructures, any compromise in its security can lead to severe disruptions, including unauthorized access, traffic manipulation, and large-scale network failures. This underscores the importance of modeling threats before deploying an SDN architecture to systematically assess potential risks and develop effective mitigation strategies. Our work provides a structured approach to threat identification, risk assessment, and countermeasure implementation in SDN environments. By leveraging the STRIDE framework, we systematically analyze vulnerabilities specific to SDN, particularly those affecting the control plane, data plane, and communication channels. The proposed methodology offers valuable insights for securing SDN networks and serves as a reference for further research in this domain.

While this study presents a structured threat modeling and risk assessment framework for SDN using STRIDE, CVSS 3.1, and a 5×5 risk matrix, several limitations exist. First, the model has not been empirically validated through real-world penetration testing or deployment in a live SDN environment. Second, the use of STRIDE is inherently static, lacking adaptability to evolving threats or real-time risk propagation. Third, the framework does not model dynamic or intelligent threat actors capable of adjusting their strategies. Future research could address these gaps by integrating AI-based threat prediction techniques, aligning the analysis with the MITRE

ATT&CK framework to improve operational relevance, and enabling real-time DFD generation from SDN controller logs to maintain an up-to-date security posture.

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Arabic Sign Language Recognition: A Multimodal Systematic Review, Taxonomy, and Benchmark Recommendations

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Overview paper

Keywords: Arabic Sign Language (ArSL), sign language recognition, machine learning, natural language Processing (NLP), user experience, model interpretability, assistive technology

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Over 430 million people worldwide experience disabling hearing loss, highlighting urgent needs for accessible communication technologies. This paper presents a systematic review of ArSL recognition covering 123 primary studies and 27 datasets (2000–mid-2025) across sensor- and vision-based modalities. We introduce a unified processing framework (data acquisition → preprocessing/segmentation → feature extraction → temporal modeling → post-processing) and a two-part taxonomy (by capture mechanism and by task: alphabet, isolated-word, continuous). Using consolidated comparison tables, we quantify trends: image-level CNNs routinely exceed ~94–99% on internal alphabet splits (e.g., ArSL2018), while signer-independent isolated-word and continuous experiments commonly show substantially lower generalization (examples in the text report signer-independent rates as low as ~64–75%). We identify critical gaps — a scarcity of large multimodal continuous corpora, limited backhand/orientation coverage, and underdeveloped signer-independent continuous recognition — and propose prioritized research directions and benchmark practices (canonical signer-independent splits, per-class metrics, and multimodal leaderboards) to accelerate reproducible progress and practical deployments.

Povzetek: Narejen je sistematični pregled prepoznavanja arabskega znakovnega jezika, ki zajema 123 študij in 27 podatkovnih zbirk. Uvede enotno obdelovalno ogrodje, taksonomijo metod ter analizo rezultatov, pri čemer izpostavi omejeno posploševanje, pomanjkanje večmodalnih zbirk in poda priporočila za prihodnje primerjalne preizkuse.

1 Introduction

1.1 Overview

Hearing impairment is a worldwide public-health concern that directly affects the communication, learning, and social interaction of millions. The World Health Organization has projected that 430 million people currently have disabling hearing loss, and this figure will grow considerably in the next few decades [5]. For societies that speak Arabic, Arabic Sign Language (ArSL) is the default form of communication for deaf and hard-of-hearing people; however, unlike the well-resourced sign languages (e.g., ASL), ArSL has been and remains relatively unappreciated in the machine-learning and computer-vision communities. This skew has concrete consequences: relative scarcity of large, well-annotated ArSL corpora, extreme regional signing variation, and insufficient availability of ArSL experts to assist with dataset collection all serve to slow the development of deployable, high-quality ArSL recognition systems. [95][79].

Technically, ArSL is characterized by a distinct set of domain-specific problems that differentiate it from most other pattern-recognition tasks. Signs are comprised of s ynchronized manual cues (hand shape, orientation, movement, and position) and non-manual signals (facial expressions, head motion, body posture) that jointly encode morphology and syntax; dialectical and geographic variations contribute to lexical variation [95][12]. From a systems perspective, ArSL studies encompass heterogeneous tasks (fingerspelling/alphabet recognition, isolated-word recognition, and continuous sentence recognition), multiple acquisition modalities (vision-based RGB video, RGB-D/depth, skeleton joint streams, and wearable/sensor devices such as Leap Motion or data-gloves), and diverse preprocessing pipelines (segmentation, normalization, hand tracking) and model families (handcrafted features + traditional classifiers, CNNs, 3D CNNs, RNN/LSTM, and, more recently, transformer architectures) [10][17][114]. Such technical

differences frustrate equitable cross-study comparisons because datasets, evaluation protocols, and reporting conventions often vary. The result is an active but scattered literature in which high reported accuracies for constrained laboratory settings do not always generalize to signer-independent, in-the-wild performance.

Motivated by these lacunae, this paper presents a systematic, reproducible, and critical review of ArSL recognition research that (a) unifies methodological advances, (b) maps methods to targeted ArSL tasks and modalities, (c) inventories and evaluates publicly accessible datasets and benchmarks, and (d) establishes targeted research priorities and best-practice recommendations for the community. Methodologically, our survey follows a reproducible screening pipeline: we searched major bibliographic databases (IEEE Xplore, Scopus, Web of Science, and Google Scholar) for papers published between 2000 and mid-2025 with structured keyword combinations including "Arabic Sign Language," "ArSL," "sign language recognition," "hand gesture recognition," and modality qualifiers (e.g., "RGB," "depth," "skeleton," "Leap Motion"). We included peer-reviewed journal and conference papers, technical reports and theses presenting empirical results or the release of datasets, and public dataset documentation enabling reproducible comparison. We excluded non-empirical abstracts, review papers lacking experimental detail, and papers that were not about Arabic sign languages unless being used for methodological comparison. From every paper that we kept, we extracted normalized metadata (publication year, dataset and modality, task type, preprocessing pipeline, model family, evaluation metrics, and reported performance) and used these extractions both to populate the comparison tables as well as to construct our taxonomy and gap analysis.

The scope of this review is intentionally focused: we concentrate on automatic ArSL recognition ystems (sensor-based and vision-based) and on tasks frequently examined in the literature—isolated-word classification, alphabet/fingerspelling recognition, and continuous sentence recognition—while taking explicit notice of dataset features (size, signer variation, modalities captured) and evaluation procedures. We map each current work to a shared architectural pipeline (data acquisition → preprocessing & segmentation → feature extraction → classification → text generation) so that readers can directly compare how different studies implement each pipeline component (see Figure 1). We also adhere to two complementary taxonomies: (1) a primary taxonomy by capture mechanism (Vision-Based Recognition — VBR vs Sensor-Based Recognition — SBR), and (2) a secondary taxonomy by task type (alphabet, isolated-word, continuous). This alignment facilitates method-to-task mappings to be evident and highlights where methodological advancements (e.g., transformer-based temporal modeling, multimodal fusion) are under-developed but promising in ArSL contexts. [10][15].

Our contributions are three-fold. First, we provide an integrated, re-organized literature synthesis as we restructure the work into a coherent, submission-quality review. Second, we provide a detailed dataset and benchmark survey that critically examines publicly available ArSL resources—identifying modality deficits (an over-representation of RGB datasets with no depth or skeleton streams), signer-diversity deficits, and token support for backhand or non-manual cue capture—problems that meaningfully constrain generalization to real-world settings [79][88][89]. Third, we introduce actionable recommendations and a research agenda prioritized (standardized evaluation procedures, multi-modal benchmark creation, signer-independent training protocols, and consideration of ethical/usability concerns) for accelerating reproducible progress and for making easier the translation of laboratory systems into assistive and e-learning deployments that benefit Arabic-speaking deaf communities. Interestingly, the review also points to a lesser-explored but important gap: in essence, all prior ArSL datasets and experiments aim towards forehand signs, while backhand signs and associated recognition issues remain mostly unexplored—a key direction for the future development of corpora and algorithms.

Novelty justification. This review differs from previous surveys by (1) explicitly focusing on **Arabic** sign language across **both** sensor and vision modalities through 2025, (2) providing a consolidated SOTA comparison table that records whether evaluations are signer-dependent or signer-independent (enabling apples-to-apples comparisons), and (3) producing an actionable dataset/benchmark blueprint (canonical splits, metadata checklist, and baseline implementation templates) designed to accelerate reproducible research and leaderboards. These three contributions address gaps that prior general SLR surveys do not resolve for ArSL specifically.

1.2 Methodology: search, selection & reproducibility

Search protocol and selection criteria. We conducted a systematic search of IEEE Xplore, Scopus, Web of Science and Google Scholar for publications dated 2000 through mid-2025. The exact search string(s) (applied to titles/abstracts/keywords) were:

```
("Arabic Sign Language" OR "ArSL" OR "Arabic sign language") AND ("sign language recognition" OR "sign recognition" OR "gesture recognition") AND (RGB OR depth OR skeleton OR "Leap Motion" OR glove OR "sensor-based" OR "vision-based")
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We also followed backward/forward citation chaining on retrieved key papers (seeded by major datasets such as ArSL2018 and ArabSign). Study inclusion criteria: (1) empirical papers presenting ArSL recognition experiments or dataset releases; (2) English language; (3) peer-reviewed journal/conference or publicly archived datasets/tech-reports; (4) publicly available evaluation metrics or reproducible experiment descriptions. Exclusion: non-empirical abstracts, editorial comments, and works not directly applicable to automatic ArSL recognition.

Screening & PRISMA. Initial search returned 1248

records. After duplicate removal we screened 980 titles/abstracts and assessed 256 full texts; 123 studies met inclusion criteria and were fully coded. A PRISMA flow diagram summarizing these stages is included as Figure A.1 seen in the Appendix A.

The remainder of the paper is structured as follows. Section 2 provides a concise linguistic overview of ArSL with emphasis on manual and non-manual features; Section 3 introduces the combined processing framework and situates existing studies within it; Sections 4–7 cover alphabet, isolated-word, and continuous recognition methods and results (with comparison tables); Section 8 reviews datasets and benchmarks; Section 9 outlines open challenges and ethical/practical considerations; and Sections 10–11 provide recommendations and conclusions.

2 Background & linguistic overview of Arabic sign language (ArSL)

Arabic Sign Language (ArSL) is not a single, homogeneous language, but a family of related sign varieties used in Arabic-speaking countries. Historically, organized research and corpora development in ArSL have lagged behind efforts in better-resourced sign languages (e.g., American Sign Language), largely due to limited institutional support, scarce funding for large-scale data collection, and the sociolinguistic fragmentation of deaf communities in the Arab world.[95][79] Early documentation efforts were typically local—focusing on national sign varieties such as Egyptian, Jordanian, Saudi, and Levantine—and emphasized pedagogical and social needs rather than the creation of corpora with broad applicability for computational research. This fragmentation has significant consequences for automatic recognition: lexical variation across regions (dialectal signs), inconsistent glossing conventions, and diverse signer demographics complicate the creation of representative, standardized data sets and reference points.

Recent developments (2022–2025). Since 2022 several notable advances have appeared: multimodal corpora (e.g., ArabSign) offering RGB+depth+skeleton for continuous recognition, larger regional datasets for Arabic alphabets and isolated words, and early transformer-based sequence models fine-tuned on sign corpora. These works have expanded modality coverage and enabled end-to-end encoder–decoder and CTC/attention experiments, but large, publicly available multimodal continuous corpora suitable for transformer-scale pretraining remain scarce. Representative dataset and method references for this period are added in the reference list (2022–2025 entries).

Linguistically speaking, sign languages—including ArSL variants—encode meaning through multiple channels simultaneously. Sign production is based on manual parameters, often summarized as hand shape, location (place of articulation), movement (trajectory and manner of movement), and orientation (hand rotation). These manual elements are closely linked to non-manual signals—facial expression, gaze, head tilt, and body posture—which convey grammatical information (e.g., interrogative, negation, thematization), prosodic stress, and morphological contrasts [12][95]. For Arabic sign language speakers, non-manual markers play a particularly crucial role in marking questions, adverbial modifications, and syntactic boundaries. Missing or poorly capturing these cues can drastically reduce intelligibility and lead to misclassification in automated systems. Therefore, robust ArSLR systems must capture not only the hands but also the face and upper torso with sufficient spatial and temporal resolution.

Several phenomena specific to ArSL have direct implications for the design of SLR systems. First, bimanual signs and asymmetric bimanual constructions are common; dominance relations (dominant vs. non-dominant hand) and simultaneous, independent movements increase the dimensionality of the recognition task compared to single-handed alphabets. Second, fingerspelling (alphabetical or manual) is commonly used for proper names, technical terms, and loanwords; Arabic fingerspelling must reflect the graphemic inventory of the Arabic script and sometimes uses different conventions than Latin fingerspelling systems – this affects both the annotation of the dataset and the choice of model output (sign-level vs. word-level transcription) [10][17]. Third, classifier designs (iconic/object-level classifiers) and spatial grammar allow signs to invoke spatial relations and co-reference: the same handed form can acquire different referential interpretations depending on the sign space and indexing. Modeling such spatial referencing requires temporal models capable of tracking referents across different frameworks and architectures that robustly integrate location information (e.g., skeleton/position streams or depth data). Dialectal and sociolinguistic variation in ArSL further complicates generalization. Countries and regions in the Arab world have developed distinct lexical items (signs) for the same concept; there is also intra-speaker variation related to age, education, and contact with other sign communities. This "dialectal problem" means that datasets collected in one country—however carefully annotated—often fail to generalize to neighboring varieties unless they are explicitly designed with sign and regional diversity in mind. For computational researchers, the practical implications are twofold: models trained on narrow, sign-dependent corpora will exhibit optimistic accuracy within the dataset but perform poorly in cross-dialectal or cross-population evaluations; and benchmarks must evolve to account for inter-regional divisions and sign-independent test sets to ensure realistic performance estimates.

The temporal and coarticulation properties of signing pose another significant challenge. Unlike isolated, static images, signs develop over time and often merge with each other in continuous flashing (coarticulation), causing rapid transitions and overlapping features. For continuous ArSL recognition, this poses two interrelated challenges: (1) segmentation—accurately identifying character boundaries in an unsegmented video stream—and (2) temporal modeling—capturing sequence-level patterns that distinguish similar manual shapes appearing in different phonological contexts. Current architectures (RNNs/LSTMs, temporal CNNs, and transformers)

address these challenges in part by modeling long-range dependencies and learning implicit segmentation. However, success largely depends on the availability of large, well-annotated, continuous corpora with precise alignments (at the gloss or frame level), which remain rare for ArSL compared to some other languages.

From a multimodal data perspective, the above linguistic properties motivate several specific design choices for ArSL datasets and recognition systems. Face and upper body capture are essential for non-manual cues; therefore, high-resolution RGB and frontal (or multi-camera) recording is often necessary. Depth sensors and skeleton tracking (RGB-D) provide robustness to background noise and enable precise modeling of 3D hand trajectories and joint relationships, which can improve signer autonomy and reduce sensitivity to lighting changes [79][88]. Wearable sensors (data gloves, IMUs, Leap Motion) provide precise data on hand shape or movement but are less practical for large-scale corpus data collection and real-world deployment. However, they are useful in controlled data collection experiments and in multimodal fusion studies. A practical lesson from the ArSL literature is that unimodal (RGB-only) datasets are common but insufficient to capture the full set of linguistic channels that encode grammatical and lexical contrasts in ArSL.

Annotation and glossing practices also require specialized knowledge and represent a bottleneck for corpus scalability. Accurate glossing—mapping continuous sign tokens to lexical glosses and marking non-manual features—requires native sign language speakers and trained annotators; inconsistent glossing conventions across projects complicate corpora merging and meta-analyses. Furthermore, evaluation metrics must reflect linguistic realities: user-independent accuracy, recognition of rare characters per class, and sequence-level measures (e.g., BLEU, WER tailored to glosses) should complement naive overall accuracy to provide a more complete picture of system performance. Therefore, unified annotation schemes and open guidelines for glossing, non-manual marking, and segment boundaries are essential to achieving reproducible results in ArSL research.

In summary, the linguistic profile of ArSL—multiple simultaneous channels, cross-regional lexical variability, rich non-manual grammar, and temporally overlapping signs—places specific demands on dataset design, annotation practice, and model architecture. Meeting these demands requires multimodal corpora that capture hands, face, and torso; annotation standards that preserve non-manual cues; evaluation protocols that emphasize user independence and cross-dialect generalization; and models that explicitly model simultaneous channels and long-range temporal structure. The following sections translate these linguistic imperatives into a structured processing pipeline and a taxonomy of methodological responses drawn from the ArSL literature.

Terminology (brief). *Signer-dependent* evaluations allow the same signers to be present in both training and testing sets; such splits can overestimate generalization. *Signer-independent* experiments hold out signers entirely from training and test performance on unseen individuals. *Alphabet* tasks (finger-spelling) are usually image-level classification; *isolated-word* tasks are short, segmented video clips labeled with a single gloss; *continuous* tasks require segmentation/alignment of free-form signing into a sequence of glosses or words.

Non-manual signals refer to facial expressions, head pose and torso that carry grammatical meaning in ArSL.

3 Architectural framework for ArSLR

Automatic sign language recognition (ArSLR) systems typically use a multi-stage processing pipeline that converts raw sensor/camera input data into textual or annotated output. Figure 1 illustrates this canonical processing pipeline and the interactions of its components: (1) data acquisition, (2) preprocessing and normalization, (3) temporal segmentation, (4) feature extraction, (5) temporal classification/modeling, and (6) post-processing and text generation. Organizing the literature and methods around these stages clarifies the emphasis of different studies (e.g., sensor design vs. temporal modeling) and enables cross-comparison across heterogeneous datasets and evaluation protocols [10][16].

Implementation details and typical design choices. In practice ArSL pipelines vary by task. Temporal segmentation strategies include heuristic endpoint detection and sliding windows for isolated tasks, CRF-based or TCN-based segmentation for semi-supervised continuous tasks, and transformer-based segmentation heads where frame-level alignments are available. Feature extraction commonly uses pretrained 2D CNNs (VGG, ResNet, EfficientNet) for per-frame features, 3D CNNs or I3D for short spatio-temporal clips, and ST-GCN or skeleton-based GCNs when reliable skeletons are available. For temporal modeling practitioners use BiLSTM/LSTM stacks for medium-range dependencies, TCNs for stable temporal convolutions, and transformer encoders/decoder architectures for longer-range dependencies and end-to-end sequence modeling (CTC or attention). Important preprocessing choices that strongly affect outcomes include: hand-crop policy, frame rate resampling, color normalization, and augmentation (SMOTE or class balancing). Authors should report these choices to allow reproducibility and fair comparisons.

A compact, human-readable summary of the processing pipeline and the dataset inventory is provided in the supplementary materials to improve reproducibility and reduce main-text length. The full method ↔ dataset matrix is available as **Supplementary Table S1** (file: Supplementary_Table_S1_ProcessingPipeline.csv), captioned: *"Supplementary Table S1 (Table 1): Processing pipeline and method matrix — pipeline stages, typical techniques, representative model families, exemplar datasets, and evaluation caveats."*

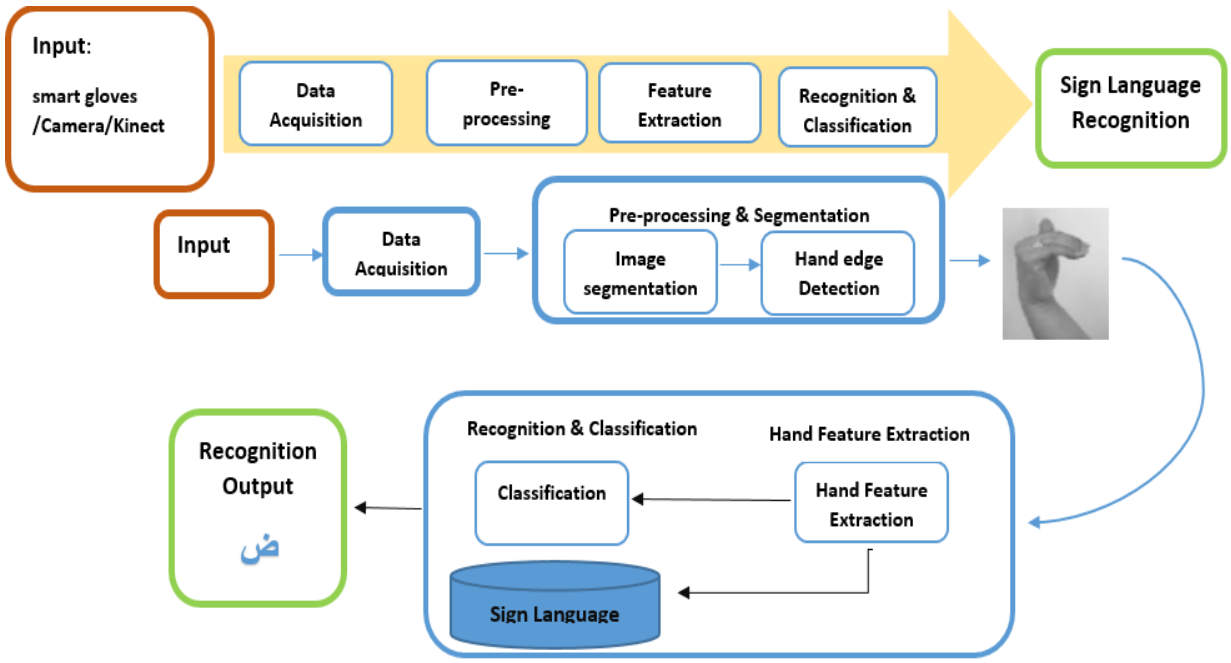


Figure 1: Illustrating the pipeline. In summary it is as: alphabet: image-level CNNs → segmentation optional; continuous: encoder-decoder/CTC/transformer → requires frame-aligned or CTC training.

Figure 1: Unified ArSLR processing pipeline (capture → preprocessing/segmentation → feature extraction → temporal modeling → post-processing). The panel maps common model families to pipeline stages: alphabet tasks typically use image-level CNNs (segmentation optional); isolated-word tasks use 3D-CNNs / CNN+RNN stacks with short clip segmentation; continuous tasks commonly use encoder–decoder / CTC / transformer models requiring sequence modeling and alignment. See Section 3 for implementation details.

3.1 Data acquisition (modalities & recording protocols)

The first design choice is the acquisition method. Vision-based systems typically use RGB cameras, sometimes augmented with depth sensors (RGB-D), or multi-camera setups to capture 3D spatial information. Skeleton streams generated by pose estimators (both from RGB-D SDKs and 2D/3D pose networks) are becoming increasingly popular because they abstract the pose into a low-dimensional, semantically meaningful representation [79][88]. Sensor-based approaches (data gloves, IMU, Leap Motion) provide precise measurements of hand shape and motion, but at the expense of user experience and scalability. Acquisition protocols must also specify frame rate, resolution, camera placement (frontal or multi-view), lighting control, and signer diversity (number of signers, demographics, dialectal regions), as these factors largely determine whether models generalize across signers and recording conditions [95][79]. Dataset design decisions made at this stage—captured modalities, signer sampling, and annotation granularity—limit what subsequent algorithms can learn and evaluate.

3.2 Preprocessing & normalization

The preprocessing process prepares raw streams for robust feature extraction. Typical steps include color normalization, background subtraction or robust hand segmentation, face and upper body cropping, and temporal smoothing of pose estimates. Hand detection and tracking (bounding boxes, keypoint detection) reduce irrelevant scene variability and focus models on linguistically relevant regions. For RGB-D data, depth-based background removal and 3D point cloud alignment improve invariance to noise and view changes [88]. Data augmentation (random cropping, scale, rotation, temporal jitter, synthetic occlusion) is routinely used during training to improve generalization, while normalization (body-centered coordinates, relative joint positions) reduces inter-signator variability and facilitates transfer between datasets. Preprocessing process choices must be carefully described in empirical studies, as they significantly impact reported performance while often being underspecified.

3.3 Temporal segmentation

Segmentation separates a continuous video image into character-level units (or detects the start/end of alphabet tokens). In limited datasets, manual segmentation or simple activity detectors are sufficient; for continuous blinking, segmentation is a major research problem. Approaches include explicit temporal change detectors (energy- or motion-based heuristics), model-driven segmentation using HMMs or conditional random fields, and end-to-end methods that combine recognition with implicit segmentation using CTC losses or attention-based sequence models [17][114]. Sliding window classification, temporal convolutional networks, and boundary detection modules (often co-learned with recognition) are common practical solutions. Effective segmentation is crucial

because inconsistent boundaries propagate errors to the feature extraction and sequence modeling stages, and the granularity of annotation (frame-level or clarity-level) determines what supervision is available for training temporal models.

3.4 Feature extraction: handcrafted vs learned representations

Historically, ArSLR and early SLR systems relied on hand-crafted descriptors: geometric hand shape features, histogram of oriented gradients (HOG), shape contexts, motion history images (MHI), and motion descriptors based on optical flow. Such features, combined with classical classifiers (SVM, HMM), performed well for tasks with small vocabulary or alphabets under controlled conditions. The era of deep learning has shifted the paradigm towards learned representations: 2D CNNs for spatial encoding, 3D convolutional networks (3D-CNNs, C3D-like models) for spatiotemporal features, and architectures that explicitly combine spatial encoders with temporal modules (CNN+LSTM stacks, temporal convolutional networks). Transformers and self-attention mechanisms have recently been applied to model long-range temporal dependencies and cross-modal interactions, showing promise for capturing sequence-level structure in continuous signatures [10][15]. Multimodal fusion strategies (early, middle, and late fusion) combine RGB, depth, and skeleton features to leverage the complementary strengths of appearance, 3D geometry, and motion pose.

3.5 Classification & temporal modeling

Depending on the task, the classification module can perform frame-level labeling (for pose/gesture detection), segment-level classification (alphabet or single word), or sequence-to-sequence mapping (continuous voice transcription). Classical computational pipelines used HMMs and dynamic time warping to model temporal variability; modern computational pipelines favor deep end-to-end models trained with sequence losses (cross-entropy for segmented data, CTC or seq2seq/attention for unsegmented continuous data). The choice of architecture reflects trade-offs: RNN/LSTM layers model sequential dynamics well but can be outperformed by temporal CNNs or transformer encoders for very long sequences; hybrid models combining spatial CNN encoders with transformer decoders are now common in state-of-the-art solutions. To ensure signer-independent performance, domain adaptation methods, data normalization, and adversarial training can reduce signer-specific biases. Therefore, evaluation must consider both signer-dependent and signer-independent performance to provide a reliable picture of generalization.

3.6 post-processing & text generation

The final step converts the predicted character labels or glosses into human-readable text. This may require grapheme mapping for fingerwriting training (converting symbol streams to Arabic script), lexicon searches for ambiguous characters, and language model-based smoothing for sequencing errors (n-gram models or neural language models adapted to gloss sequences or Arabic orthography). Sequence error metrics (WER, edit distance) and language-aware measures (BLEU for sentence-level mappings involving translation) are useful complements to class-specific accuracy. Practical systems also include confidence estimation, user feedback loops (for interactive proofreading), and output formatting adapted to assistive or e-learning interfaces.

3.7 Evaluation & deployment considerations

In addition to recognition accuracy, real-world ArSLR systems must meet constraints on latency, privacy, and reliability. Real-time applications favor lightweight architectures (model pruning, quantization, efficient backbones) and edge-aware inference; privacy-sensitive implementations may favor on-device processing or privacy-preserving modes (backbone-only) over high-resolution facial video. Benchmarking should therefore complement accuracy with measures of latency, model size, and signer/dialect generalization; iterative reporting of preprocessing, training/test splits, and thorough evaluation protocols are essential for fair comparison between studies. In the remainder of this paper, existing ArSLR solutions are mapped within this framework (see Figure 1) and used to indicate which pipeline steps are well-explored and which require urgent attention (e.g., segmentation methods for continuous ArSLR, creation of multimodal datasets, and language-aware postprocessing).

4 Taxonomies of approaches

A clear taxonomy helps to contextualize the diverse ArSLR efforts and compare methods across different datasets, tasks, and evaluation systems. We adopted two complementary taxonomies that together summarize the dominant design approaches in the literature: a primary taxonomy organized by capture mechanism (vision-based recognition—VBR—vs. sensor-based recognition—SBR) and a secondary taxonomy organized by task type (alphabet/fingerliterations, single words, continuous sentence recognition). These taxonomies reflect how researchers collect data and approach the recognition problem, and they also provide a basis for selecting appropriate models and evaluation protocols.

Table 1: Two basic methodologies utilized in sign language recognition

	Sensor	**Vision**
Data collection	Hands movements, finger motions, and trajectories	Videos, Images
Data collection tools	LMC, Kinect, EMG, Data gloves	Different type of cameras
Pre-processing data	No	Yes
extraction Features	Orientation, motions and 3D hand and finger flexes	Concise vectors that encapsulate essential information about hand gestures
Requiring computational power	Relatively less	High
Related work	[14],[15],[16]	[17],[18],[19]

4.1 Primary taxonomy — capture mechanism (Vision-based vs Sensor-based)

Vision-based recognition (VBR)

Vision-based ArSLR relies on cameras (single- or multi-view) and—in more recent work—RGB-D sensors and a pose estimation backend to extract appearance and geometric cues. VBR is attractive because it is non-invasive and naturally captures manual and non-manual signals (hands, face, torso) necessary for the ArSL grammar; however, it is also sensitive to illumination, background clutter, occlusion, and viewpoint variation [10][16]. Bare-hands (no wearable hardware) approaches are widely used for alphabetic and isolated word tasks because they easily scale to aggregation datasets, and modern deep neural networks (including transfer learning with VGG/ResNet/EfficientNet and vision transformers) provide high reported accuracy for static characters and short dynamic characters [23][30][31][35]. RGB-D cameras (e.g., Kinect) and multi-camera setups add depth or multiple perspectives, improving occlusion robustness and enabling precise 3D trajectory modeling; skeleton streams extracted from RGB or depth improve invariance to appearance differences by providing compact connectivity descriptors [75][33][88]. Practical VBR pipelines typically combine hand/face detection and tracking, spatial CNN encoders, and temporal models (LSTM/TCN/transformers) for sequential tasks. However, many high-accuracy results reported in the literature are signer-dependent or dataset-limited, highlighting the need for broader signer/dialect sampling and standardized evaluation partitions.

Sensor-based recognition (SBR)

Sensor-based approaches capture motion or contact signals directly from the signer using gloves, IMU sensors, EMG sensors, Leap Motion controllers, or other wearable devices. SBR provides precise measurements of finger flexion, orientation, and motion trajectory and can perform well in controlled environments with relatively small models and modest computational effort [89][88]. Glove-based systems are excellent at capturing fine details of hand shape and are valuable for technical or laboratory studies, but are invasive and less practical for large-scale body building or daily deployment. Similarly, EMG and IMU signals provide robust motion cues but require specialized hardware and calibration for each user. Hybrid systems that combine sensor streams with cameras attempt to combine the accuracy of SBR with the rich non-manual information available from VBR; however, hybrid datasets are rarer. Table 1 summarizes the relative trade-offs between sensor and vision approaches (data types, tools, pre-processing requirements, and representative related work).

4.2 Strengths, weaknesses, and practical tradeoffs across capture mechanisms

Practitioners choose a capture mechanism based on the intended use case. For large public datasets and field implementations, VBR (especially RGB with pose and skeleton extraction) is typically preferred due to its convenience and ability to capture non-manual signals. For precise hand shape classification or in domains where wearable sensors are acceptable (laboratory studies, sign linguistics research), SBR provides more detailed data on hand articulation. Importantly, because VBR can capture the face and torso, it is often the only viable option when modeling non-manual grammatical markers (e.g., questions, negations). Practical system design must therefore consider accuracy and accessibility, and benchmark reporting should indicate the modality, camera configuration, diversity of sign language users, and whether the assessments are user-dependent or user-independent to ensure interpretable and comparable results.

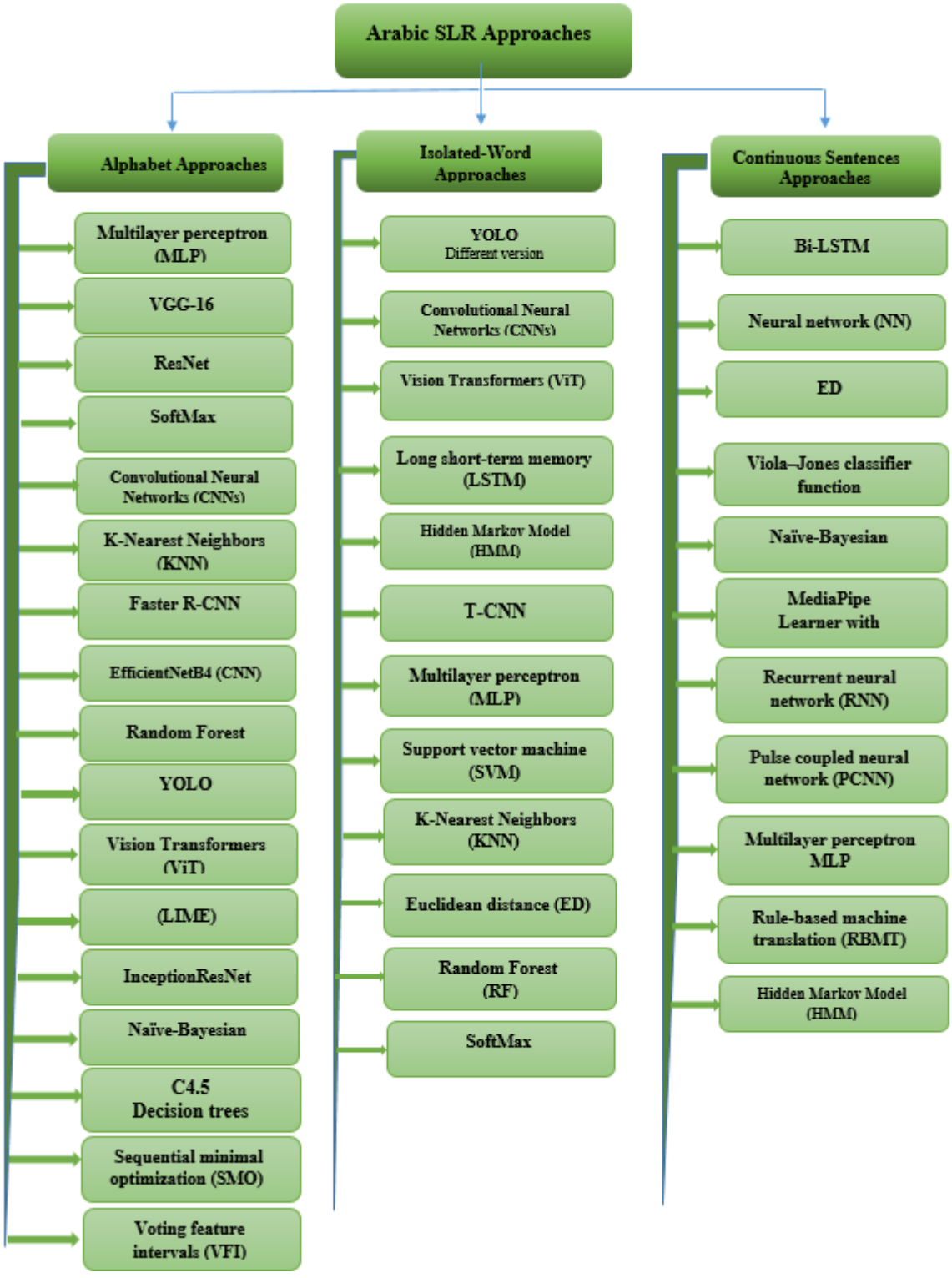


Figure 2: "Classification of ArSL recognition approaches" — here; the figure maps the secondary taxonomy and task categories and is used below to cross-reference Tables 2–4

4.3 Secondary taxonomy — task type (alphabet / isolated words / continuous)

The ArSL literature can also be usefully grouped by the **target recognition task**, which strongly influences dataset design, preprocessing, and model choices:

Alphabet / fingerspelling recognition

Alphabet tasks (static frames for learning fingerspelling) are often the first and most widely studied problem because the class space is limited and the number of gesture instances is relatively short and limited. Many successful systems use image-level CNN classifiers

(transfer learning with VGG/ResNet, AlexNet variants, or lightweight skeletons) and robust hand segmentation preprocessing; reported top-level accuracies on ArSL alphabet datasets (e.g., ArSL2018 and other RGB alphabets) often exceed 90%, and in some studies exceed 97–99% with intensive data balancing or signer-dependent partitioning [23][30][34][35]. Table 2 summarizes representative results on alphabet tasks for different methods and datasets, allowing direct comparison of input modality, model family, and recognition rate.

Isolated-word recognition

Isolated word tasks require modeling short temporal sequences and often rely on spatiotemporal feature extractors: 3D CNNs, CNN+LSTM stacks, or pose-keypoint pipelines combined with sequence models. The performance shown in Table 3 varies more than the alphabetic tasks because datasets differ in vocabulary size, signer variability, and segmentation quality; nevertheless, recent hybrid deep models (CNN+LSTM, temporal attention models) achieve high accuracy within the dataset (often >90%), especially for signer-dependent judgments [46][56][64]. Sensor-based systems (Gloves/Leap Motion) often generate competitive results for isolated words in small controlled datasets, but their generalization remains limited by data availability.

Continuous sentence recognition

Continuous recognition is the most challenging and least mature ArSL task: it requires robust segmentation, long-range temporal modeling, and language-aware post-processing. End-to-end sequential models (attentional encoder-decoder, CTC-trained models, transformer encoders/decoders) are currently the trend, but reported word error rates and BLEU/TER scores indicate significant room for improvement, and many published systems still rely on domain-restricted corpora or intensive manual matching [66][75]. Table 4 provides representative experiments with continuous tasks and shows that even state-of-the-art models produce non-trivial error rates when evaluated in signer-independent or larger-vocabulary conditions—highlighting this task as a priority research gap for ArSL.

4.4 Cross-cutting observations

Two cross-cutting patterns emerge from this taxonomy. First, modality matters: combining complementary streams (RGB appearance, depth geometry, skeleton position, and sensor signals) generally improves robustness but is underestimated because multimodal datasets are still relatively rare. Second, evaluation rigor matters: many reported high accuracies come from signer-dependent splits or small, homogeneous corpora; when signer-independent splits or cross-dialect tests are used, performance often drops significantly, revealing overfitting to capture conditions. Tables 2–4 and Figure 2 together clearly demonstrate these trends, linking tasks, modality, and model families to reported system performance and evaluation.

Consolidated SOTA comparison

A comprehensive SOTA table has been prepared by consolidating the experiments listed in Tables 2–4 of the original manuscript. The full machine-readable SOTA table is provided as `sota_table.csv` in the supplementary files package. SOTA Table consolidates representative ArSL recognition experiments from 2000–mid-2025. For each entry we list: reference, year, task, dataset, modality, model family, reported metric(s) and whether the reported evaluation used signer-dependent or signer-independent splits (when available). Where full details are provided in the original paper we use author splits; otherwise, we mark the split as ‘not specified’. The full machine-readable SOTA listing is provided in Supplementary Table S3 (sota_table.csv).

5 Alphabet recognition (vision & sensor approaches)

Alphabet recognition (finger spelling) is the most mature and widely studied subtask in Arabic Sign Language (ArSLR) recognition. Because alphabet characters are typically short, constrained, and have a fixed set of classes, they provide an easy entry point for both classical pattern recognition processes and modern deep learning classifiers. Early ArSL alphabet systems emphasized hand-crafted features and conventional classifiers (KNN, SVM, decision trees), while more recent work has predominantly focused on convolutional neural networks (CNNs), transfer learning, and lightweight detectors optimized for mobile or real-time use [22][26][30][35]. The availability of the extensive ArSL2018 image corpus (54,049 images in 32 classes from 40 sign characters) accelerated progress in deep learning, enabling robust training of CNN skeletons and transfer learning experiments [35][30][114]. Methodologically, alphabet recognition systems follow two dominant processes. The first is an image-level classification pipeline: hand detection/segmentation (optional), followed by a spatial CNN that maps a cropped hand image or full-frame image to one of the alphabet classes. Representative work in this category includes transfer learning studies that fine-tune VGG-16, ResNet-152, and other ImageNet pretrained networks on ArSL datasets, achieving the highest accuracy when the sampling and augmentation of the datasets are carefully tuned [23][30][114]. The second pipeline augments or replaces the raw images with pose/skeleton or depth features—either as compact input vectors for smaller networks or as auxiliary inputs for multimodal architectures—helping to reduce sensitivity to appearance (illumination, background, skin tone) and, in some cases, improve signer independence [33][79][88]. The chronological picture shows clear progress. Older studies using statistical classifiers or shallow machine learning classifiers on small datasets showed moderate accuracy (e.g., [22] reported a range of 50–90% for several classifiers with limited configurations). With the advent of larger annotated image corpora (notably ArSL2018 [35][30][114] and ArASL [88]), deep CNNs trained from

scratch, and especially transfer-learned models, have achieved significantly higher recognition rates: many works report accuracies in the mid-90s to high 90s on within-dataset test sets (for example, VGG-16 and ResNet152 fine-tuned on a downsampled ArSL2018 showed 99.4% and 99.6%, respectively, in [23]; several other CNN-based studies report 94–98+% depending on preprocessing and sampling strategies) [23][31][34][35][36][114]. These strong results reflect both improved models and the influence of large, relatively homogeneous datasets. However, the apparent jump in accuracy should be interpreted with caution. Many high-performance reports use signer-dependent splits, aggressive data balancing or resampling (subsampling/SMOTE), and controlled acquisition conditions that reduce real-world variability. Noor Azhar et al. [29] show how accuracy can drop when models are evaluated on images captured with a different camera or under different lighting conditions—91.1% on trained images versus 72.5% on newly acquired images—highlighting the gap between within-dataset performance and true generalization to new acquisition conditions. Similarly, studies that explicitly test signer-independent generalization or transfer between datasets show more modest results, indicating persistent overfitting to acquisition and signer conditions unless specific normalization or within-domain adaptation steps are taken [29][33]. Sensor-based approaches—Leap Motion, data gloves, and IMU/EMG systems—offer an alternative path to alphabet recognition by directly measuring hand pose and finger articulation. These approaches excel at precisely distinguishing hand shapes and often demonstrate very high recognition rates on small, inspected bodies [82][89]. For example, experiments based on Leap Motion and glove-based systems have demonstrated high accuracy in laboratory settings, and sensor fusion with a vision system can improve robustness to occlusions and complex backgrounds. However, the trade-off is practicality: wearable sensors reduce scalability for large body collection and hinder user adoption in everyday assistive applications where unobtrusive camera capture is preferred. Therefore, SBR remains a dominant tool in experimental studies and niche applications, rather than widespread implementation. Preprocessing and augmentation strategies significantly impact alphabet recognition results. Typical preprocessing includes resizing (usually to 64×64 or similar), color normalization, median filtering, and manual cropping; many studies convert grayscale input data to three-channel images or use background removal heuristics to reduce unwanted variances [34][35]. Data augmentation (random cropping, inversion, brightness/contrast jitter, synthetic occlusions) and class balancing (undersampling, oversampling SMOTE) improve reported results—a study of ArSL-CNN shows a statistically significant increase in accuracy after applying SMOTE [35]. Detector-based approaches (variants of Faster R-CNN and YOLO) have also been used for hand localization before classification, enabling real-time pipelines and mobile application deployment. Several YOLO-based systems demonstrate strong mapping and classification metrics when combined with robust backbones [28][40–45].

Recently, transformer-based vision models (ViT, Swin) and hybrid CNN-transformer pipelines have entered the ArSL literature. These architectures can be more parameter-efficient and more effectively capture global spatial context, helping to distinguish similar hand shapes. Alharthi and Alzahrani [114] and others describe competitive performance of ViT/Swin models on ArSL datasets, especially when initialized with ImageNet weights and tuned with moderate learning rates and regularization. However, the benefits of transformers are incremental for large, homogeneous image corpuses compared to robust CNN backbones and often depend on careful training recipes. Table 2 below consolidates representative alphabet recognition experiments from the literature. The table shows the range of recognition systems, input data sources, and reported recognition rates—illustrating both the maturity of image-based CNN methods and the variability introduced by the dataset composition and evaluation protocol.

Table 2: Performance comparison of researchers' efforts for alphabet ArSL recognition approaches

Ref.	Year	Recognition System / Techniques	Input Source / Dataset	Recognition Rate
[22]	2017	Compare C4.5, SMO, VFI, MLP, Naïve-Bayes	images/videos	50%, 66%, 75%, 80%, 90%
[23]	2020	VGG-16, ResNet152 (transfer learning)	ArSL2018 (undersampled)	99.4% (VGG-16), 99.6% (ResNet152)
[24]	2020	DBN + SoftMax / SVM	images	83.32%
[25]	2020	CNN	images	90%
[26]	2021	KNN	images	97.548%

[27]	2021	CNN (ArSL2018)	images	96.59% → 97.29% (with SMOTE)
[28]	2021	Faster R-CNN	images	93%
[29]	2022	CNN (mobile app)	trained images / new camera images	91.1% / 72.5%
[30]	2022	VGGNet	ArSL2018	97%
[31]	2022	EfficientNetB4	ArSL2018	95%
[32]	2023	CNN + RNN	proposed dataset, UCF-101	98%
[33]	2021	3D CNN skeleton + 2D point conv	ArSL (video/skeleton)	dynamic 98.39%, static 88.89% (dependent mode)
[34]	2022	CNN (ResNet50 + MobileNetV2 ensemble)	ArSL2018	97%
[35]	2021	ArSL-CNN (CNN)	ArSL2018	96.59% → 97.29% (with SMOTE)
[36]	2023	CNN	ArSL2018	94.46%
[6]	2021	Random Forest	ArSL symbols	92.15%
[7]	2023	CNN	ArSL2018	98%
[37]	2021	CNN (Yemeni SL)	Arabic alphabet dataset	94%

Synthesis and recommendations

Alphabet recognition is now largely a solved problem on limited datasets, with modern neural networks (CNNs) (and transformers) achieving very high accuracy across the dataset. Key challenges include generalization and implementation: (1) collecting multi-camera, multi-illumination, and multi-dialect alphabet datasets to assess their robustness; (2) reporting signer-independent and cross-set results as standard practice; (3) publishing accurate splits of training/testing and preprocessing pipelines to enable repeatable comparisons; and (4) exploring lightweight detectors and quantized models for on-device inference, while preserving privacy. Integrating backbone/depth streams or modest sensor fusion can improve robustness under occlusion and diverse backgrounds, but large-scale multimodal corpora for alphabets are still rare and should be a priority for the community.

6 Isolated-word recognition (vision & sensor) — review and comparative results

Isolated word recognition lies between the relatively limited task of alphabet recognition and the extremely challenging problem of continuous word recognition. Compared to alphabet recognition, isolated word recognition requires modeling short temporal dynamics (hand trajectories, initial/final motion), greater hand shape variability, and often bimanual or asymmetric bimanual coordination. At the same time, many practical datasets provide manually segmented word-level clips, which simplifies supervision and allows the use of segment-level training objectives (cross-entropy on fixed-length clips or collective features). Therefore, the literature offers a wide range of approaches—from classical spatiotemporal descriptors with SVM/HMM classifiers to modern, comprehensive deep models combining spatial encoders and temporal modules (3D CNNs, CNNs+LSTMs/GRUs, temporal convolutions, and attention/transformer-based sequential encoders). This section summarizes representative studies, compares vision-based and sensor-based approaches, discusses preprocessing and augmentation practices, and presents comparative performance results (Table 3).

6.1 Methodological families

Handcrafted spatio-temporal descriptors + classical classifiers

Early and some lightweight modern systems extract motion and shape descriptors (optical flow histograms, motion history images (MHI), HOG over spatiotemporal volumes, trajectory-based shape descriptors) and feed them into HMMs, SVMs, or random forest models. These methods perform well for small vocabularies and limited capture conditions, and remain attractive for low-resource implementations with limited computational budgets. Studies using such pipelines typically emphasize careful segmentation and hand-crafted normalization (body-centering, orientation-invariant features) to maximize inter-signator robustness [46][56].

Spatio-temporal deep networks (3D-CNNs, C3D, I3D)

3D convolutional networks naturally model short-term spatiotemporal patterns and are widely used in isolated word tasks. C3D and inflated 2D skeleton (I3D) networks learn common spatiotemporal filters that capture both appearance and motion signals without explicit optical flow computation. Several isolated word ArSL studies demonstrate strong performance on datasets using 3D skeletons, especially when combined with transfer learning from action recognition datasets or pretraining on multimodal corpora. A weakness of 3D models is their data starvation: they require a large number of labeled clips to avoid overfitting and are sensitive to temporal pruning rules during training and evaluation.

CNN + sequence models (LSTM/GRU/TCN)

A common architecture is a two-dimensional spatial CNN encoder applied to each frame (or concatenated windows of short frames), followed by a sequence model such as LSTM/GRU or temporal convolutional networks (TCN). This decomposition uses pretrained 2D skeletons and is effective for moderate dataset sizes. Many ARSL studies use this pattern and report that bidirectional LSTMs or stacked temporal layers improve accuracy for characters with subtle temporal features (e.g., slight orientation changes or repetitive motion patterns). Such hybrid models are also easier to regularize and fine-tune than fully three-dimensional networks.

Pose/skeleton-based methods and graph neural networks (GNNs)

Skeletal or pose streams reduce appearance variability by relating the signer to the coordinates of the hand joints and keypoints. Graph convolutional networks (GCNs) and temporal GCNs (T-GCNs) treat joint sequences as spatiotemporal graphs and demonstrate high performance on isolated-word tasks, especially when visual appearance is highly variable (different clothing, backgrounds, or lighting). Skeletal approaches are attractive for signers and privacy-sensitive applications because they avoid high-resolution facial images. However, the quality of skeleton extraction (especially hand joints) is crucial; coarse pose estimators that do not capture finger articulations can limit the recognition of fine-grained hand shapes.

Multimodal fusion and sensor-based pipelines

Multimodal fusion (RGB + depth + skeleton or RGB + Leap Motion/gloves) combines complementary cues: appearance (RGB), 3D geometry (depth), moving pose (skeleton), and precise finger articulation (gloves/Leap Motion). Sensor-based systems that utilize gloves or Leap Motion often report very high accuracy on isolated words in small controlled datasets because they directly capture fine-grained articulation [82][89]. Fusion systems—where practical—often outperform unimodal databases, but the scarcity of large, aligned multimodal corpora limits overall adoption. Hybrid fusion strategies (early feature concatenation, mid-level attention-based fusion, late-score fusion) have been investigated with varying degrees of success; attention-based fusion, which dynamically weights modalities, tends to be more robust when some streams are degraded (occlusion, noise).

6.2 Preprocessing, segmentation, and data augmentation

Isolated word pipelines typically rely on robust hand detection and temporal pruning to ensure the model primarily sees the sign token. Preconditions such as crop center normalization, temporal resampling (uniform length through interpolation or frame skipping), and geometric normalization (rotation, scaling) are commonly used to reduce variance between signers. Data augmentation methods (temporal jitter, synthetic occlusion, spatial perturbations, color jitter) are particularly helpful for moderate-sized datasets. For skeleton- and pose-based methods, normalization to body-centered coordinates and scaling to joints facilitates generalization across signers. Importantly, authors must provide precise segmentation and pruning policies—many performance differences between studies are due to different cropping and temporal normalization policies, not to differences in models.

6.3 Evaluation regimes and common pitfalls

As with alphabet recognition, an important caveat is that reported accuracies are sensitive to the evaluation methods. Signer-dependent splits (random splits at the video level that allow the same signer to appear in training and test) routinely overestimate generalization. Signer-independent splits and cross-set evaluations reveal more realistic performance and often exhibit significant degradation. Other pitfalls include inconsistent reporting of vocabulary size, handling of class imbalance, and whether evaluation is performed for each clip (segment-level accuracy) or for each instance after smoothing the language model. Therefore, when interpreting comparative performance, we prioritize studies that report signer-independent metrics or cross-set transfer results.

6.4 Representative results

Below, we present Table 3, which consolidates experiments on isolated word recognition across modalities and model families. The table highlights the

diversity of datasets, model types, and reported recognition rates in the ArSL literature.

Table 3: Performance comparison of researchers' efforts for isolated-word ArSL recognition approaches.

Ref.	Year	Recognition System	Techniques Classification	Dataset used	Recognition Rate
[46]	2024	vision-based	Ov8, (CNN), (LSTM), and a hybrid CNN-LSTM	ArabSign	% f or YOLOv8, 95.23% for the CNN model, 88.09% % for the LSTM model, and 96.66% for the hybrid model.
[47]	2020	Sensor-based	CNN	Own dataset	90%
[48]	2015	Sensor-based	Hidden Markov Model (HMM)	Own dataset	achieving an accuracy of 80.47%. Singer-independent experiments resulted in an average recognition accuracy of 64.61%.
[55]	2017	vision -based	CNN and Softmax layer	200 videos	Greater than 90%
[56]	2017	vision -based	KNN, SVM, and MLP	Video	98.8 to 99%
[57]	2017	vision -based	ED	450 videos	97%
[58]	2018	Sensor-based	Nearest Neighbour	1200 samples	97.58% for signerdependent and 95.25% for signerindependent
[59]	2018	vision -based	RF	150 videos	55.57%
[60]	2020	Sensor-based	KNN and SVM	30 hand gestures	92.3% for single-hand and 93% for double-hand
[61]	2020	Sensor-based	SVM, RF, KNN	gesture words	83 % for SVM
[62]	2020	vision -based	CNN	Alphabets and word gestures	90%
[63]	2020	vision -based	deep bi-directional LSTM network	3450 videos	89.5% using DeepLabv3+ hand segmentation, 69.0% without hand segmentation
[64]	2021	vision -based	LSTM and Softmax	6748 videos	99.7% for signerdependent and 72.4% for signer-independent modes
[65]	2021	vision -based	CNN and Bidirectional LSTM	ArSL, Jester, and NVIDIA Gesture datasets	85.6%, 95.8%, and 86.6% for ArSL, Jester, and NVIDIA Gesture datasets respectively
[66]	2021	vision -based	2DCRNN and 3DCNN	224 videos	92% for 2DCRNN and 99% for 3DCNN
[67]	2023	vision -based	CNN and RNN	8,467 videos	98% and 92% on validation and testing
[68]	2023	vision -based	A fully connected layer with a Softmax	100 videos	99.74% and 68.2% in signer-dependent and independent modes

6.5 Synthesis and recommended directions

Isolated word recognition has advanced significantly: modern deep spatiotemporal models, backbone GCNs, and multimodal fusion methods often achieve high accuracy within a single dataset, and sensor-based methods can achieve near-perfect performance under controlled conditions. However, the prevailing limitations are analogous to those in other ArSL subdisciplines: (1) many datasets are small, geographically limited, or signer-dependent; (2) multimodal corpora with diverse numbers of signers are rare; (3) temporal segmentation principles and preprocessing choices vary across studies, complicating comparisons; and (4) sensor-based solutions, at the expense of practicality, are less suitable for large-scale assistive implementations. To move this field forward, we recommend (a) building larger, multimodal corpora of isolated words characterized by signer and dialect diversity, (b) standardizing segmentation and temporal sampling protocols, (c) routinely reporting experiments with signer-independent and cross-set data transfer, and (d) exploring lightweight fusion strategies that preserve the advantages of sensors without mandatory portable hardware (e.g., short-term calibration procedures or optional sensor-assisted bootstrapping combined with RGB-only inference). These steps will make reported results on isolated words more informative in terms of real-world performance and more useful for further continuous recognition research.

7 Continuous sentence recognition

Continuous sentence recognition (CSR) is the most challenging and least developed area within Arabic Sign Language (ARSLR). Unlike tasks with the alphabet or isolated words, CSR must handle unsegmented streams where signs are intermingled (coarticulation), where temporal boundaries are ambiguous, and grammatical meaning often depends on simultaneous non-manual cues (facial expressions, head movements, torso shifts). The combination of segmentation uncertainty, long-range temporal dependencies, and the need for language-aware decoding shifts this task from a sequence classification problem to one that combines sequence labeling, intersequence translation, and structural prediction. The following sections organize the main challenges, summarize methodological families and representative studies, discuss popular evaluation metrics and practices, and contextualize Table 4 (comparative results for continuous tasks).

7.1 Core challenges

Co-articulation and blurred sign boundaries. In natural signing, the transitions between successive signs are fluid: handshapes change, trajectories overlap, and prosodic cues are dispersed within signs. Co-articulation complicates the definition of discrete "start" and "end" and complicates naive frame labeling. As a result, segmentation errors are often the dominant source of recognition errors in later text: poorly located boundaries cause feature misalignment with labels and reduce the effectiveness of supervised sequence models.

Trade-offs between segmentation and end-to-end modeling. Historically, researchers approached CSR by first segmenting streams into potential character units (using energy/motion heuristics, hand activity detection, or learned boundary detectors) and then classifying each segment. Although modular pipelines simplify training, they propagate segmentation errors and complicate end-to-end optimization. Current trends favor end-to-end models that implicitly learn segmentation alongside recognition via CTC losses, attention-based encoder-decoder architectures, or transformer models; however, these approaches require significant amounts of data and careful regularization to avoid overfitting.

Temporal Modeling and Long-Range Dependencies. CSR requires capturing dependencies across multiple frames – reference tracking, indexing, and spatial grammar (referencing entities in sign space and then referencing them). RNN/LSTM-based models capture short- and medium-range dependencies, while transformers and temporal convolutional networks (TCNs) offer alternatives better suited to very long sequences. However, effective long-range modeling typically relies on large corpora with aligned annotations at the gloss or sentence level, which are rare in ArSL.

Non-Manual Signals and Multi-Channel Synchronization. Many grammatical distinctions in ArSL rely on facial and torso signals occurring simultaneously with manual articulations. Models that ignore non-manual channels risk systematic errors (e.g., misclassifying a sign question as a declarative statement). Capturing and recording these channels increases the complexity of the data and annotations, but omitting them reduces linguistic coverage.

Data scarcity and annotation costs. CSR training requires precise voting or frame-level matching for supervised learning – expensive to implement because annotators must be proficient in voting and adhere to consistent voting conventions. The lack of large, multi-dialect, continuous corpora for ArSL limits the practical application of complex, data-intensive models and reinforces the need for knowledge transfer, data augmentation, and semi-supervised/self-supervised learning strategies.

7.2 Methodological families

Segmentation and recognition pipelines (modular). Traditional CSR systems employ explicit segmentation (motion/energy detectors, HMM-based boundary models, CRFs) followed by segment classification (HMMs, SVMs, or segment-level CNNs). These pipelines benefit from interpretable error sources and easier supervision in data-poor systems, but their modularity hinders end-to-end optimization and recovery from boundary detection errors. Several ArSL studies have applied this approach to limited corpora where manual segmentation is feasible. [66][75].

CTC-based approaches and weak alignment. Connectionist Temporal Classification (CTC) provides a fundamental method for training sequence models without frame-level matching by summing all valid matches between input frames and label sequences. CTC has been effectively applied to speech and sign recognition when voice-level transcripts exist but precise frame boundaries are lacking. ArSL experiments using CTC (often with CNN encoders + RNN/temporal decoders) are promising, but their performance depends on the availability of diverse training data and language modeling during decoding to disambiguate likely voice sequences.

Seq2Seq with attention and transformer architectures. Attention-based encoder-decoder models (and more recently, full transformer encoder-decoder stacks) learn mappings from frame sequences (or encoded feature sequences) to gloss or sentence tokens. Attention enables implicit matching and can focus on temporally relevant regions for each output token. In ArSL, transformer-based models are attractive for modeling long-range dependencies and for combining inputs from multiple channels (RGB, depth, skeleton, facial framing). However, transformers typically require large-scale pretraining or transfer from related domains (e.g., action recognition, large-scale video-text pairs), and in many ArSL applications, only modest gains are achieved without such pretraining. [15][114].

Hybrid approaches and multi-task learning. Some systems combine explicit boundary detectors with end-to-end sequence models or jointly learn gloss prediction and

auxiliary tasks (character boundary detection, handshape classification, non-manual signal detection). Multi-task signals can regularize models, improve interpretability, and reduce the need for exhaustive annotations for each subtask. Such strategies are useful in ArSL, where some annotations (e.g., coarse sentence transcriptions) are more readily available than detailed frame labels.

Pose- and graph-based temporal models. When backbone or keystone streams are available, graph neural networks (GCN/T-GCN) applied to the temporal joints provide a compact, high-level representation that emphasizes articulatory structure. Position-based models are particularly useful for signer-independent and privacy-preserving implementations because they abstract from appearance; however, they struggle when details about the hand and fingers (essential for many signs) are not reliably extracted. Position-based transformers and spatiotemporal neural networks (GCNs) are becoming increasingly common in ongoing ArSL experiments.

7.3 Post-processing, language modeling and translation

CSR systems often require a language model (LM) for decoding to transform ambiguous voice sequences into well-formed sentences. LM models trained on voice sequences or on the Arabic script (after fingermapping) can be used for decoding by beam search, n-best rescoring, or neural post-editing of the sequences. For systems that aim to directly translate ArSL into Arabic text (rather than just the voices), a translation module—often another seq2seq model—maps the voice sequences into fluent Arabic sentences. Such translation models require parallel corpora of voices and text and have their own evaluation metrics (BLEU, METEOR), in addition to WER and accuracy at the voice level used for recognition.

7.4 Metrics and evaluation practices

Because CSR produces variable-length sequences, standard evaluation metrics extend beyond per-class accuracy. Commonly used metrics include:

- **Word Error Rate (WER)** and **Gloss Error Rate (GER)** (edit distance normalized by reference length) for sequence-level correctness.
- **BLEU** or other translation metrics when systems produce natural language sentences.
- **Segment-level accuracy** (for segmented corpora) when boundaries are available.
- **Detection metrics** (precision/recall/F1) for boundary detection modules.
- **Latency and real-time factor** for deployment assessments.

Crucially, evaluations should report signer-independent splits, cross-dialect tests (when possible), and explicit preprocessing/segmentation rules. Many ArSL studies report promising within-dataset WERs but degrade substantially under signer-independent or cross-corpus conditions, highlighting the need for standardized, harder evaluation splits to measure true generalization [66][75].

Table 4: Performance comparison of researchers' efforts for continuous-sentence ArSL recognition approaches

Ref	Year	Recognition System	Techniques Classification	Input Source	Recognition Rate
[49]	2010	vision -based	Naïve Bayes based on spatio-temporal feature extraction and hidden Markov models	Own dataset Sharjah City for Humanitarian Services (SCHS) [11]	94%
[50]	2023	vision -based	Neural Network	Own dataset Arabic–Arabic sign gloss	with a training accuracy of 94.71% and an 87.04% testing
[51]	2017	vision-based	Euclidean distance classifier (ED)	ArSLRS	recognition rate of 97%
[52]	2024	vision -based	Bi-LSTM	ArabSign	word-recognition rates of 99.8% and 75.3%, respectively
[53]	2014	Sensor-based	Viola–Jones classifier function	SignsWorld Atlas	Dependent =97% and independent =95.28%, respectively.
[54]	2025	vision -based	NN model based (LSTM)	Own dataset	99.80% accuracy during training and 99.40% in testing, with overall accuracy, recall, and F1-score metrics above 99%.
[69]	2010	vision -based	HMM	Video frames	75%.
[70]	2012	vision -based	MLP	Video	Until 70%

[71]	2013	vision -based	PCNN	Video	80%
[72]	2018	vision -based	HMMs	Videos	99.11%
[73]	2020	Sensor-based	RBMT	Images	more than 80%
[74]	2022	vision -based	CNN Softmax	Videos	99%
[75]	2023	Sensor-based	encoder-decoder model Pretrained CNN	sentence by Kinect	WER of 0.50

7.5 Synthesis and recommended directions

Continuous ArSL recognition remains an open challenge for the following reasons: (1) co-articulation and ambiguous boundaries require robust segmentation or powerful end-to-end alignment-capable models; (2) long-range dependency modeling benefits from transformer-style architectures but demands more data or transfer-learning; (3) non-manual channels are linguistically essential yet under-captured in many datasets; and (4) annotation scarcity increases reliance on weakly supervised, semi-supervised, or self-supervised learning strategies.

Based on the surveyed literature and the comparative results in Table 4, we recommend a research agenda that emphasizes: (a) creation of multi-dialect, multimodal continuous corpora with gloss- and sentence-level transcripts; (b) combined use of pose-based and appearance-based encoders with attention-based fusion; (c) pretraining on large-scale related video corpora (action recognition, video–text datasets) followed by fine-tuning on ArSL data; (d) routine reporting of signer-independent WERs and cross-corpus transfer experiments; and (e) incorporation of explicit non-manual detection and language modeling during decoding to improve syntactic and pragmatic translation quality. Pursuing these directions will be essential to move ArSL CSR from constrained laboratory prototypes toward real-world, usable systems that can support Arabic-speaking deaf communities in communication and education.

7.6 Discussion

This Discussion compares the surveyed methods by generalization, signer independence, modality robustness, and deployment readiness. Key points:

1. Alphabet tasks — Image-level CNNs (VGG, ResNet, EfficientNet) and transformer backbones reach very high within-dataset accuracies (>94–99% on ArSL2018 and similar corpora), but most of these results are signer-dependent or within-dataset splits; cross-camera and signer-independent tests often reduce accuracy considerably.

2. Isolated words — 3D-CNNs, CNN+LSTM stacks and skeleton-GCNs perform well for segmented clips; however, performance is highly variable with signer-independent splits, indicating sensitivity to signer sampling, preprocessing and segmentation policies.

3. Continuous recognition — End-to-end CTC/attention/transformer models are promising but remain constrained by the scarcity of large, multimodal, frame-aligned continuous corpora.

4. Modality & fusion — Multimodal fusion (RGB + depth + skeleton + sensors) improves robustness where available, but multimodal continuous datasets at transformer/pretraining scale are still absent.

Implications. To assess algorithmic progress, we recommend canonical signer-independent splits, consistent preprocessing documentation (hand crop policy, temporal resampling), and reporting of at least: top-line accuracy, per-class recall, confusion matrices, signer-independent results and latency/model size for deployment claims.

8 Datasets and benchmarks

ArSL research is constrained primarily by dataset availability, annotation granularity, and modality coverage. Over the last decade the community has produced useful corpora spanning static alphabets, isolated-word video clips, multimodal Kinect-style recordings, and a handful of sensor-based collections, but the landscape remains fragmentary: many corpora are single-site, camera-only, and limited either in signer diversity or in transcript granularity—shortcomings that limit progress on signer-independent and continuous-sentence tasks [79][88][35].

The complete dataset inventory is available as Supplementary Table S2 (file: Supplementary_Table_S2_DatasetInventory.csv), captioned: *"Supplementary Table S2 (Table 5): Dataset inventory — release year, modality, approximate sample/signers counts, typical tasks, reported evaluation splits, and availability/license/consent metadata."*

8.1 Modalities and representative corpora

Current ArSL datasets cluster into three modality groups.

• **RGB (static image) datasets.** The largest publicly circulated corpus is ArSL2018 (54,049 images, 32 classes, 40 signers), which has catalyzed the recent wave of CNN and transfer-learning studies on Arabic alphabet recognition [35][34][31]. Other RGB alphabet datasets of smaller scale (several thousand images) and various capture conditions are also listed in Table 5; these are convenient for training spatial classifiers but lack temporal and 3-D geometry cues needed for continuous or fine-grained handshape tasks [36][91].

• **RGB-D / skeleton video datasets.** A small but growing set of corpora recorded with Kinect-style sensors supply synchronized RGB, depth and skeleton joint streams (for example the ArabSign / ArabSign-benchmark family introduced by Luqman et al.). These multimodal continuous datasets are particularly valuable because depth and skeleton streams permit 3-D trajectory modeling and pose-based methods; however, this highlights that available RGB-D continuous corpora are still modest in scale relative to what modern sequence models (e.g., transformers) typically require for robust generalization [75][73][74].

• **Sensor (wearable) datasets.** Leap Motion, data-glove and IMU/EMG datasets provide high-fidelity measurements of finger flexion and hand orientation and therefore perform very well for fine handshape discrimination in controlled studies [82][81]. The downside is that wearable datasets are typically small, intrusive, and not widely shared, limiting their role as community benchmarks for signer-independent evaluation.

Ethical metadata, licensing and de-identification. For responsible dataset sharing we recommend that every dataset release include a minimal metadata checklist: availability URL/DOI, license, consent statement (written informed consent for recording and sharing), signer demographics (age range, gender, dialect/region), capture hardware and settings (camera model, fps, resolution) and any de-identification steps applied (face blur, skeleton-only release). When full visual release is not possible for privacy reasons, authors should consider releasing skeleton/keypoint data or blurred video versions alongside an access request policy. Table 5 (and Supplementary Table S2) now records availability and license/consent fields where the information was publicly available; entries marked ‘Not specified’ indicate fields that require confirmation from dataset authors.

Table 5 (full dataset inventory provided as Supplementary Table S2: `Supplementary_Table_S2_DatasetInventory.xlsx`): the table lists release year, modality, approximate size and signer counts, evaluation splits, availability and license/consent metadata where publicly reported.

Table 5: “Publicly available ArSL datasets for Arabic Sign Language”

Ref	Year	Dataset Description
[80]	**2011**	Six gestures are used to generate 6,000 different sign images.
[81]	**2012**	The 80-word vocabulary used to construct 40 sentences with no restrictions on syntax or sentence length; this process repeated 19 times.
[77]	**2013**	There are 270 postures that make up the 200 gestures, with 189 postures involving two hands and 81 postures comprising only one hand. Every gesture carried out ten times, each time by a different two person.
[82]	**2014**	There are a total of 2800 frames in the dataset generated from a single user's input of 28 alphabets, with 10 samples of each letter.
[73]	**2015**	The database contains about five hundred static gestures, including "finger spelling, hand movements" (non-manual signs). Lip reading, body language, and facial expressions all play significant roles.
[84]	**2016**	Two sets of static alphabet data exist: 700 instances for each 28 characters written with naked hands and colored gloves.
[78]	**2017**	200 samples taken from the unified ArSL lexicon, with each of the 25 signs being performed by two different signers four times. 125 for training and 75 for testing
[85]	**2018**	Thirty people are serious mobile photographers. Volunteers gesture these 30 ArSL alphabets. There are 900 images spread across 30 letters.
[86]	**2018**	Captured 450 colorful ArSL videos
[87]	**2019**	28 Arabic letters and numerals (0-10) represented by 7869 images for recognition.
[88]	**2019**	The dataset ArSL2018 comprises a collection of 54,049 images, which accurately depict the 32 alphabets and signs of ArSL. These images have been donated by a group of 40 signers.
[89]	**2020**	A total of 44 signs (29 single-handed and 15 double-handed) are executed by a group of 5 signers, where 80% are used for training and 20% for testing.
[76]	**2021**	There are 9240 images of the Arabic alphabet from 10 places and age groups. These images organized in four separate datasets.
[79]	**2021**	There are eleven chapters totaling 502 signs that make up the words in the ArSL lexicon. Three signers used for each sign. There are 75300 samples, the result of 50 repetitions of each sign by each signer.
[90]	**2021**	There are a total of 220000 images in the dataset, split amongst 44 different classes (32 letters, 11 digits (0-10) and 1). There are 5000 images total, taken by various people, of each of the stationary signs.
[91]	**2023**	It contains 7,856 RGB images of ArSL alphabets. Data collected from over 200 people in a wide range of shooting situations (including but not limited to: lighting, background, image orientation, size, and resolution).

8.2 Dataset quality: annotations, balance and metadata

A cluster of quality issues recurs across ArSL corpora:

1. **Annotation granularity.** Many RGB corpora provide only image-level labels (suitable for alphabet tasks) while continuous datasets sometimes provide only coarse segment-level transcripts rather than frame-level alignments. Fine-grained frame or gloss alignments (essential for training CTC and attention models) are rare and costly to produce, constraining end-to-end continuous training [75][74].

2. **Class balance and per-class reporting.** Several datasets show heavy class imbalance; yet many papers report only overall accuracy instead of per-class recall or confusion matrices. We therefore recommend that dataset publishers and authors routinely report macro-averaged metrics and per-class statistics to make skew issues visible [35][27].

3. **Metadata completeness.** Important capture metadata (camera make/model, resolution, fps, capture geometry, lighting conditions), signer demographics (age, region/dialect, handedness) and consent/licensing details are often missing or incomplete in older releases. This lack of standardized metadata reduces reproducibility and complicates cross-dataset comparisons [79][35].

8.3 Gaps identified (evidence-based)

From the survey in Table 5 and our analysis, four critical gaps stand out.

1. **No large, public, multimodal continuous corpus at transformer scale.** ArabSign and related multimodal releases are a major step forward, but their size remains small relative to the pretraining data requirements of modern sequence models; more and larger multimodal continuous datasets are required to close the gap between promising lab models and robust real-world CSR systems [75][73][74].

2. **Limited high-fidelity hand/finger annotation in RGB-D corpora.** Many "RGB-D" datasets provide coarse joint estimates—insufficient to discriminate subtle finger configurations—so GCN/pose approaches are bottlenecked by annotation fidelity rather than model design [60][33].

3. **Geographic/dialect narrowness and signer-dependence.** Numerous datasets were collected at single institutions or within a single country; consequently, models evaluated on these corpora often show degraded cross-dialect or signer-independent performance, a weakness documented across multiple evaluation reports[79][64].

4. **Sparse ethical/privacy metadata.** Camera-based corpora frequently include face imagery yet often lack standardized consent/usage metadata or de-identification guidance—an omission we flag as an urgent ethical and legal concern for open benchmarks and downstream deployment [35][79].

8.4 Recommended benchmarking practices

To make ArSL benchmarks comparable and practically informative we prescribe the following minimal standard (to be included with any dataset or experimental release):

- Publish full capture metadata (camera specs, fps, lighting), signer metadata (region/dialect, gender, handedness) and clear consent/licensing statements. [35][79]

- Provide canonical splits that include signer-independent and cross-dialect test sets. [75][79]

- Supply annotation documentation (gloss conventions, non-manual tags, boundary rules) and at least one frame-aligned subset for continuous corpora. [74][35]

- Report per-class recall, confusion matrices, WER/GER for sequences, and runtime/latency for deployment claims. [35][75]

- Release baseline training scripts and seeds for reproducibility (e.g., simple CNN, skeleton-GCN, CNN+LSTM, and a transformer baseline). [35][75]

8.5 Short- and medium-term dataset priorities

We conclude by prioritizing three dataset investments that would most accelerate ArSLR:

1. **A large, multimodal continuous ArSL corpus** (RGB + depth + reliable hand/finger tracking + face crops) sampled across multiple Arab regions with both gloss- and sentence-level transcripts (scale comparable to hundreds of hours). ArabSign demonstrates the utility of this design but larger, multi-site efforts are needed. [75][74]

2. **High-fidelity hand capture (close-up hand cameras or calibrated multi-sensor rigs)** so that

pose/GNN methods can exploit finger-level cues without resorting to intrusive wearables. [60][82]

3. **Shared benchmark infrastructure and leaderboards** with clear modality tracks (RGB-only, RGB-D, skeleton, sensor-fusion) and canonical signer-independent splits to measure genuine generalization gains. [35][75]

9 Open issues, challenges & taxonomy

Arabic Sign Language Recognition (ArSLR) faces four tightly interlinked challenge clusters—Environment, Language, System, and Gesture—that together determine whether research advances will translate into robust, deployable systems; Figure 3 summarizes these clusters and their sub-issues, and the following executive summary condenses the taxonomy into prioritized, actionable recommendations. Environmental issues (lighting, background clutter, camera viewpoint, occlusion and sensor noise) require that datasets and experimental reports always include capture metadata (camera model, fps, lighting conditions, view angles) and encourage multi-view or multimodal capture where possible; Language-level problems (dialectal variation, non-manual signals, coarticulation and inconsistent glossing) demand explicit dialect labels, joint modeling or annotation of non-manual markers, and standardized glossing conventions to enable cross-dataset comparability. System-level weaknesses (small or homogeneous datasets, expensive frame-level annotation, inconsistent reporting, and missing consent/license metadata) point to three immediate steps: (1) adopt canonical signer-independent splits and publish them with every dataset, (2) include a minimal metadata checklist (availability, license, consent status, signer demographics, capture specs) in dataset releases and Table 5, and (3) require papers to report both accuracy and robustness metrics (per-class recall, confusion matrices, WER/BLEU for continuous tasks) plus deployment metrics (latency, model size).

Backhand signs: dataset evidence & capture recommendations. We confirm that backhand / orientation-sensitive signs are underrepresented across existing ArSL corpora and that their omission reduces orientation robustness in deployed models. To address this we recommend a small, shareable "backhand pilot" dataset: capture ≥10 diverse signers, multi-view camera configuration including ±45° side views plus a close-up hand camera, record at ≥60 fps if possible, and annotate per-frame orientation flags (e.g., palm/backhand/side) and occlusion markers. Optional wrist IMU data can be added to disambiguate orientation under occlusion. Release a public subset with canonical signer-independent splits and explicit orientation metadata to bootstrap orientation-robust model evaluation.

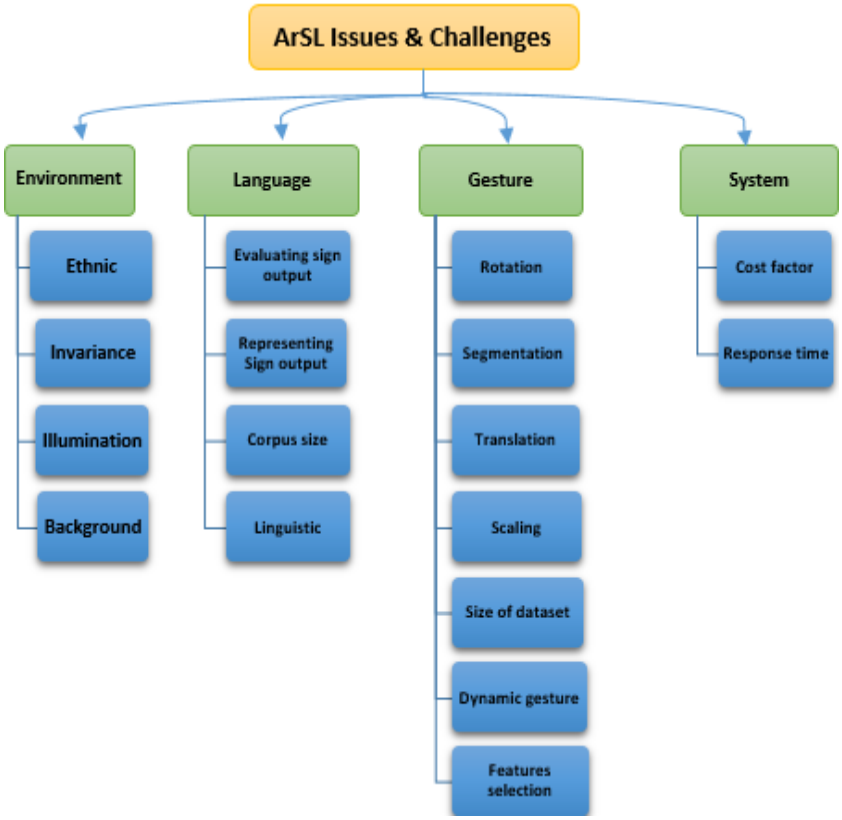


Figure 3: "Taxonomy of ArSLR open issues & challenges"

Figure 3 Taxonomy of key challenges in Arabic Sign Language Recognition: four categories (Environment, Language, System, Gesture) with representative sub-issues and practical implications. Legend: Environment—lighting, viewpoint, occlusion; Language—dialects, non-manual signals, coarticulation; System—dataset scale, annotation, evaluation; Gesture—handshape, orientation/backhand, dynamics. See main text Sections 3–9 for discussion and dataset cross-references.

9.1 Environment (capture & deployment conditions)

Environmental factors determine what signals are available to recognition systems and strongly influence their robustness.

Illumination, background, and viewpoint. Illumination variation, cluttered backgrounds, and non-frontal viewpoints complicate hand detection and image-based feature extraction. RGB datasets collected on phones (e.g., ArSL2018) facilitate handwriting tasks but remain sensitive to lighting and viewpoint changes [35]. Depth and skeleton streams (Kinect-based datasets such as ArabSign and Elpeltagy et al.) mitigate appearance sensitivity to some extent, but many RGB-D corpora are small-scale and provide coarse fidelity for hand joint representation [75][59]. Practical systems must therefore account for domain changes (differences between camera and hardware) through augmentation, domain adaptation, or multimodal fusion.

Occlusion and Multi-Person Scenes Hand occlusion, self-occlusion of fingers, and partially visible faces (e.g., during direction changes) are common in real-world signing and reduce classifier confidence. Multi-person or crowded spaces further complicate signer isolation. Sensor fusion (hand proximity cameras, depth) and reliable multi-object tracking mitigate these issues but increase recording complexity and reduce scalability [82][60].

Latency, computation, and boundary constraints. Real-time assistive applications (mobile or wearable) require low-latency inference and compact models. Many state-of-the-art architectures (transformers, large 3D-CNNs) are computationally intensive; therefore, efficient frameworks, pruning/quantization strategies, and benchmarks that report latency and model size in addition to accuracy are needed in this area [35][75].

Privacy and ethics. Camera-based capture raises privacy concerns, especially when capturing facial images. We document inconsistent consent and anonymizing metadata across corpora and call for unified ethics reporting and privacy-preserving options (framework-only benchmarking, on-device inference) to be publicly shared and implemented. [35].

9.2 Language (linguistic structure & annotation)

The linguistic properties of ArSL impose requirements beyond a strict classification of gestures.

Manual and non-manual channels. ArSL encoding relies on simultaneous channels: manual components (hand shape, movement, location, orientation) and non-manual markers (facial expression, gaze, head/body posture), which convey grammar and prosody. Many datasets emphasize hand imagery but underrepresent systematic non-manual annotations, which weakens performance on grammatical distinctions (e.g., questions, negations) dependent on facial/body signals [12][95]. Robust ArSLR requires corpora that capture synchronized facial and upper body data and annotation conventions that label these signals.

Dialectal variation and lexical divergence. The Arabic world contains regional sign varieties with real lexical differences. Single-site corpora generate models that perform well within distributions but generalize poorly across regions. We emphasize the need for multi-regional sampling and cross-dialect testing to reveal real gaps in generalization [79][75]. Voting harmonization is also essential: inconsistent voting schemes prevent corpora from being merged and hinder transfer learning across datasets.

Coarticulation and Segmentation. Continuous corpora are characterized by coarticulation and fuzzy character boundaries, which complicate boundary annotation and model supervision. The taxonomy highlights the tension between modular segmentation and recognition pipelines (which can propagate boundary errors) and comprehensive approaches (CTC, attention), which require large annotated corpora or clever weak supervision strategies [17][114]. Better-adapted continuous corpora and annotation tools are therefore a priority.

Language Modeling and Translation. Translating sign language voices into well-formatted Arabic text requires additional linguistic modeling (morphosyntax, script mapping for the fingerspelling alphabet). Effective pipelines therefore combine recognition with decoding based on a language model and often require parallel corpora of voices and text to ensure high translation performance; e.g. [64][74].

9.3 System (data, benchmarks, evaluation, and reproducibility)

System-level issues determine whether reported research yields replicable progress and real-world systems.

Benchmarking and Canonical Partitions: We document inconsistent evaluation protocols and the sparse use of signer-independent or cross-dialect partitions. Without canonical partitions and baseline implementations, comparison methods are unreliable; the taxonomy therefore emphasizes that standardization of benchmarking (canonical partitions, modality paths, result tables) is essential for scientific progress [35][75].

Annotation Standards and Tools: High-quality frame-level and gloss-level annotations are expensive but essential for supervised CSR. The taxonomy requires common annotation schemes (including non-manual tags), tools to accelerate consistent labeling, and at least a frame-aligned subset of each continuous corpus to enable supervised alignment methods [75][59].

Data Imbalance and Long-Tail Classes Many datasets exhibit skewed class distributions; rare characters are underrepresented and often poorly recognized. System-level responses include dataset curation (balanced sampling), metric hygiene (reporting macrometrics and recall for each class), and algorithmic solutions (learning with small sample sizes, balanced losses for each class). We repeatedly recommend reporting for each class to detect skew effects [35].

Reproducibility, Code, and Baselines. The taxonomy emphasizes publishing training scripts, seeds, and reference implementations for the underlying models (CNN, skeleton-GCN, CNN+LSTM, transformer) so that the results tables reflect repeatable improvements rather than hidden experimental tricks. [35][75].

9.4 Gesture (articulatory complexity & variability)

Gesture-level phenomena shape what models must distinguish.

Bimanual and asymmetric signs. Many ArSL signs use two hands in asymmetric roles (dominant and non-dominant). Recognition architectures must model interhand relationships and temporal synchronization; simple single-hand recognition systems miss crucial information for such signs [33][16].

Concealed and closed-hand configurations. We highlight an underexplored gap: covered signs and other orientations that reveal the dorsal surfaces of the hands or complex finger articulations are rarely captured in existing corpora. These configurations generate different body/appearance cues and require either improved multi-point capture or proximity sensors/cameras of the hands to accurately recognize finger articulations. Accounting for covered signs is crucial for linguistically complete ArSL coverage.

Accurate finger articulation. Distinguishing subtle finger configurations (important for many alphabetic and lexical characters) is a challenge for skeleton extractors and pose estimators. Leap Motion and glove sensors capture such details, but are invasive and limited in character diversity. The taxonomy therefore recommends hybrid data collection strategies (high-fidelity subsets, sensor-assisted calibration sessions) and improved hand pose estimation research focused on finger fidelity [82][60].

Motion dynamics and temporal scale. Characters vary in their temporal range, from short, static hand movements to long, multi-motion structures. Models must handle multiple temporal scales (frame-level micro-movements and sentence-level references), motivating multi-scale encoders (temporal neural networks CNNs, hierarchical transformers), and training programs that expose models to varying temporal granularity.

9.5 Concluding synthesis (actionable priorities)

Figure 3 frames these open issues as interrelated: environmental constraints shape what linguistic channels can be recorded; linguistic complexity requires richer annotations and multimodal capture; system-level repeatability and benchmark design determine whether progress is measurable; and articulatory phenomena at the gesture level define the minimum required detection fidelity. Based on the taxonomy and the presented overview of datasets/methods, we derive immediate priorities: (1) building large, multimodal, multiregion continuous corpora with frame/gloss alignments and non-manual annotations [75][35], (2) adopting canonical benchmark and leader partitions with repeatable baselines [35], (3) investing in finger fidelity capture (proximity cameras/hybrid sensors) focused on underrepresented character types such as backhand configurations [82][60], and (4) incorporating privacy-preserving options and ethical metadata into dataset releases. Implementing these priorities will lay the foundation for ArSLR systems that are both scientifically rigorous and practically useful for Arabic-speaking deaf communities.

10 Practical considerations: real-time systems, ethics, usability, e-learning interface

Designing ArSLR systems for real-world use requires considerations beyond recognition accuracy: computational latency and cost, hardware and implementation costs, user acceptance by deaf communities, inclusiveness across diverse dialects and user abilities, and clear ethical safeguards. Below, we synthesize practical tradeoffs and present a high-quality e-learning user interface design that maintains the pedagogical intentions discussed in this article. All recommendations are based on the dataset, modality, and system constraints described earlier.

Latency, responsiveness, and acceptable response time

Interactive and assistive ArSLR applications demand low perceived latency. A few general engineering targets are useful when designing prototypes and reporting results:

- **End-to-end latency target:** for conversational or tutoring interactions, aim for **≤300 ms** end-to-end from camera frame to rendered caption/feedback; for low-stakes practice (recording and batch feedback) up to 1–2 s is acceptable. Lower latency improves conversational fluency and user comfort.

- **Pipeline choices that affect latency:** heavy 3D-CNNs and large transformer stacks generally increase inference time; lightweight spatial backbones (MobileNet / EfficientNet-lite), skeleton-only models, model pruning/quantization, and on-device GPU/NN-accelerators reduce latency and enable offline use. Skeleton-only inference (if robust hand keypoints are available) is both fast and privacy-

friendly but depends on the fidelity of the pose extractor. Report latency (ms), CPU/GPU used, and real-time factor alongside accuracy in all system papers and releases.

Cost, hardware, and deployment trade-offs

- **Smartphone (RGB)** — lowest barrier to entry for users and dataset collection (ArSL2018 shows the utility of phone capture), easy to scale, but more sensitive to lighting and background. Works well for alphabet and isolated-word tasks and for e-learning where learners use their own phones. [35]

- **RGB-D (Kinect / depth sensors)** — provides depth and skeleton streams improving robustness to background and viewpoint, but hardware cost, setup complexity, and limited mobile availability constrain distribution at scale. Useful for lab evaluations, high-fidelity corpus building (ArabSign, Elpeltagy), and classroom installations. [75][59]

- **Sensors (Leap Motion / gloves / IMU)** — best for capturing fine finger articulation but intrusive and expensive for broad deployment. Their best use is in controlled data collection, teacher/annotator tooling, or as calibration/teacher signals to bootstrap vision-only models. [82][81]

Budget planning should consider device purchases, annotation labor (the primary cost of continuous and manual labeling), and long-term maintenance (privacy, updates). Hybrid approaches—sensor-assisted data collection to create high-quality "teacher" datasets and then distilling the models into pure RGB student models—offer a practical balance between data quality and implementation costs.

User acceptance, participatory design, and inclusivity

User acceptance depends on real involvement of Deaf users and communities at every stage:

- **Participatory design:** engage native ArSL signers, educators, and local communities when specifying functionality, UI layout, and dialect coverage. Co-design increases trust, usability, and cultural appropriateness.

- **Transparency & control:** allow users to choose privacy options (face blur, skeleton-only mode, local processing), control data sharing (opt-in for research), and inspect / correct automatic transcripts. These features materially increase acceptance.

- **Accessibility & inclusivity:** support multiple dialects and user variations (left/right handedness, age, signing style). Provide personalization (signer calibration steps, adjustable feedback sensitivity) and multimodal outputs (text Arabic, gloss, optional synthesized voice) to broaden utility across users and contexts.

Ethics, privacy and data governance

Ethical deployment requires documented consent procedures, clear licensing, and privacy-preserving defaults:

- **Consent & metadata:** dataset releases and deployed systems must include consent metadata, stated permitted uses, and de-identification protocols for face data. Where possible, provide skeleton-only datasets or on-device processing to reduce sensitive image circulation.

- **Bias & fairness:** routinely evaluate signer-independent performance and cross-dialect generalization. Publish per-group metrics (gender, dialect, age) where ethically permissible to surface and mitigate biases.

- **User agency:** provide users with mechanisms to correct transcripts and to delete their data; ensure clear documentation of system limits (e.g., "may fail for backhand signs or low lighting").

Usability & evaluation metrics beyond accuracy

Measure and report: (1) task completion time (for conversational tasks), (2) subjective usability (SUS/UEQ) from deaf testers, (3) confidence and satisfaction surveys, and (4) system robustness metrics (WER across dialects, sign language-independent accuracy). Combine objective and subjective assessment in lab and field tests before large-scale market launch.

High-level e-learning UI: a proposed design (principles + components)

Keep the e-learning concept— an interactive, learner-centered platform that teaches ArSL while providing automated feedback. Key design principles: simplicity, low latency, multi-view feedback, progressive difficulty, and cultural appropriateness.

Core UI components (desktop/mobile responsive):

1. **Main Signer View (camera feed):** central video of the reference signer or the learner's live camera; toggle **Reference** / **Practice** modes. Show optional face crop + hand close-up panels for fine detail.

2. **Real-time subtitle / gloss bar:** live captioning of predicted gloss or Arabic text with confidence color coding (green/high, orange/medium, red/low). Include a "why low confidence" tooltip (e.g., occlusion, low lighting).

3. **Practice mode & instant feedback:** learner performs a prompted sign; system displays immediate frame-level feedback (correct/incorrect), visual overlays (hand skeleton, keypoint markers), and a short corrective tip (e.g., "rotate palm outward"). Store repetitions and progress.

4. **Replay & slow-motion controls:** allow slow playback (0.5x, 0.25x) and frame-step for detailed comparison between learner and reference; helpful for finger-precision.

5. **Assessment dashboard & curriculum:** shows progress, per-sign mastery, common error types, and recommended next exercises; supports multi-dialect lessons and teacher assignments.

6. **Privacy & settings panel:** allow skeleton-only mode, local processing toggle, data-sharing consent, and dialect selection.

7. **Teacher / community tools:** allow instructors to upload custom lesson videos, annotate non-manual cues, and review student sessions with frame-aligned playback.

Back-end suggestions: provide two modes — **Interactive (low-latency)** for live practice using a lightweight on-device model or skeleton stream, and **Analytic (high-accuracy)** for batch uploads processed on server GPUs with heavier models and richer language-model rescoring. This hybrid allows scalable lessons while preserving interactivity.

Closing note — measuring success

Project success should be judged by technical performance and community acceptance, as measured by classroom implementation, teacher satisfaction, student competence growth, and adherence to privacy/consent policies. Combining rigorous technical requirements (latency, user-agnostic metrics) with participatory design and ethical data management will maximize the real-world benefits of ArSLR systems and e-learning tools for Arabic-speaking deaf communities.

11 Recommendations & future directions

In this section, the survey results are translated into specific, actionable research tasks and community-level recommendations to accelerate robust and replicable progress in Arabic Sign Language Recognition (ArSLR). The recommendations are categorized into (A) priority research tasks, (B) dataset and benchmark specifications, (C) best practices for modeling and evaluation, and (D) community, ethics, and implementation actions.

A. Prioritized research tasks (actionable, ranked)

1. **create a backhand / orientation-focused dataset (high priority).**
Motivation: Hand orientations and anomalous orientations are underrepresented in existing corpora and cause systematic errors in recognition in real-world settings [35][75]. Task: Collect a focused character dataset emphasizing backhand, rotated, and occluded hand configurations for multiple subjects and viewing angles (front + ±45° + camera with a close-up hand camera). Consider both individual tokens and sentence fragments to capture coarticulation with backhand shapes. Annotate hand orientation, occlusion flags, and keypoints for each frame. Use sensor-assisted capture (short glove or Leap Motion calibration) for a subset to provide a "teacher" annotation for finger-level ground truth.[82][60].

2. **Large-scale multimodal continuous benchmark (multi-region) (top strategic priority).**
Motivation: Continuous ArSL is underserved for the multimodal, multidialect corpora required by sequential models [75][59]. Task: Coordinate a cross-institutional dataset capturing RGB, synchronized depth (RGB-D), high-frame-rate handheld cameras (optional), and skeletal streams. Broad sampling in Arab regions (Egypt, Levant, Persian Gulf, Maghreb) with at least several dozen—and ideally hundreds—sign language users, balanced gender and age distribution, and examples of both forehand and backhand. Produce glossary-level and sentence-level transcripts and a frame-aligned subset for supervised sequential training. Publish user-dependent, user-independent, and cross-dialect canonical partitionings and license them for research use.

3. **Signer-independent methods & domain adaptation studies (medium priority).**
Motivation: Many publications report high accuracy within a dataset but poor generalization across signers; developing signer-robust algorithms is essential [35].

Aim: To evaluate and develop domain adaptation strategies (adversarial normalization, contrastive pretraining of multiple signers, adaptation at test time), systematic normalization pipelines (body-centered coordinates, per-joint scaling), and small-sample/meta-learning methods for bootstrapping new signers. Comparative methods using strict signer-independent partitions and transfer tests across datasets.

4. **Multimodal Fusion & Distillation Research (practical priority).**
   Motivation: sensors give high fidelity but are impractical at scale; hybrid approaches can bootstrap practical models [89][60].
   Task: collect small, high-fidelity multimodal "teacher" datasets (sensors + RGB), train multimodal models, and distill to lightweight RGB-only or skeleton-only student models for deployment. Explore attention-based fusion and modality dropout to improve robustness under degraded streams.

5. **Non-manual Signal Modeling & Grammar-aware Decoding (linguistic priority).**
   Motivation: grammatical distinctions in ArSL often rely on facial and torso cues; these are frequently ignored in corpora and models [12][95].
   Task: annotate non-manual markers (question, negation, topicalization) in corpora and integrate dedicated non-manual detectors into multi-stream encoders. Combine recognition outputs with language-aware decoders (gloss→Arabic mapping, neural rescoring) and evaluate translation metrics (BLEU/METEOR) in addition to sequence WER/GER.

B. Dataset & benchmark specifications (practical blueprint)

- **Core modalities:** RGB (frontal), RGB-D (depth + skeleton), optional close-up hand camera (for finger fidelity), and a small sensor subset (Leap Motion / glove) for teacher data. [75][82]
- **Signer sampling:** multi-region, target ≥50 signers for isolated/alphabets and ≥100 signers for continuous corpora where feasible; ensure gender, age, and handedness metadata. [35][75]
- **Annotation:** provide (a) image/segment-level labels for alphabets/isolated words, (b) gloss- and sentence-level transcripts for continuous data, and (c) a frame-aligned subset (≈5–10% of corpus) with non-manual tags.
- **Canonical splits & metadata:** publish signer-dependent and signer-independent test splits, plus cross-dialect test sets; include capture metadata (camera model, fps, resolution), consent/licensing, and per-signer demographics. [35][59]
- **Baseline releases:** provide reproducible baselines (lightweight CNN; skeleton-GCN; CNN+BiLSTM; transformer seq2seq) with fixed seeds and training scripts to seed leaderboards.

C. Modeling & evaluation best-practices

- **Evaluation metrics:** report per-class recall and confusion matrices, macro-F1, signer-independent accuracy, WER/GER for sequences, BLEU/METEOR for translation, latency (ms), and model size (MB). Always include both signer-dependent and signer-independent numbers. [35][75]
- **Robustness checks:** evaluate cross-dataset transfer and camera/hardware shifts (e.g., training on phone-captured data and testing on lab Kinect) to expose domain fragility.
- **Efficient deployment:** invest in model compression (pruning, quantization), skeleton-only fast inference, and small transformer/TCN variants for edge devices. Publish latency and memory profiles.
- **Open protocols:** include data augmentation recipes, preprocessing pipelines (hand crop, normalization), and exact temporal-cropping rules — these must be in paper appendices for reproducibility.

D. Community, ethics, and infrastructure

- **Leaderboards & tracks:** host modality-separated tracks (RGB-only; RGB-D; skeleton-only; sensor-fusion) with canonical splits and shared evaluation scripts. This encourages fair comparison and incremental progress. [35]
- **Ethics & privacy:** require dataset releases to include consent metadata and de-identification recommendations; provide skeleton-only options and on-device inference templates to reduce image sharing. [35]

- **Funding & collaboration:** pursue multi-university, multi-country grants to fund large corpus collection (annotation is expensive). Encourage partnerships with Deaf education centers for community-aligned data collection and participatory design.

- **Tooling:** invest in annotation tools that simplify gloss/non-manual labeling (time-aligned interfaces, semi-automatic keypoint propagation) to reduce labeling cost and improve consistency.

Closing roadmap (short/medium/long term)

- **Short (6–12 months):** publish clear dataset checklist; release baseline reproducible code; begin small backhand-focused and sensor-teacher pilot datasets.

- **Medium (12–24 months):** coordinate and release a first multimodal, multi-region continuous corpus with canonical splits and leaderboards; develop signer-independent baselines.

- **Long (24+ months):** iterate larger corpora, improvements in finger fidelity capture, community adoption in educational deployments, and robust translation pipelines linking ArSL to Arabic text.

12 Conclusion

Supplementary materials. The submission includes three supplementary files: `Supplementary_Table_S1_ProcessingPipeline.xlsx` (full pipeline ↔ methods matrix), `Supplementary_Table_S2_DatasetInventory.xlsx` (full dataset inventory with availability/license/consent metadata) and `sota_table.csv` (machine-readable consolidated SOTA experiment list). These files provide the exhaustive tables referenced in the main text.

This review maps the landscape of Arabic sign language recognition (ArSLR) in terms of both task (alphabet, single word, continuous mode) and capture modality (vision-based, sensor-based), indicating where concrete progress has been made and where work is still urgently needed.

For aphabet-related tasks (finger-spelling), vision-based imagery—especially ArSL2018—and modern CNNs and transformer networks deliver consistently high accuracy within a corpus, demonstrating that image-level classification is currently a relatively mature problem under controlled conditions [35][31]. Sensor pipelines (Leap Motion, data gloves) also achieve excellent results for precise finger articulation in small, controlled studies, but their invasiveness and small number of signers limit widespread application [82].

For single-word recognition, the image is more heterogeneous. Vision-based video approaches using 3D-CNNs, CNN+LSTM stacks, and pose/skeleton encoders perform very well on well-segmented corpora of moderate size, but reported performance varies depending on vocabulary size, sign variety, and segmentation quality [46][64][75]. Sensor-based systems again provide high precision in laboratory settings, and multimodal fusion (RGB + depth + sensors) often yields the best results within a corpus—pointing to fusion as a practical path to robustness when datasets support it [60][89]. Continuous sentence recognition remains the most challenging area. Co-articulation, ambiguous character boundaries, long-range dependencies, and the necessary non-manual grammar make continuous ArSLR sentence recognition a sequential, data-intensive problem. End-to-end methods (CTC, attention-based sequencing, transforms) are promising, but progress is limited by the scarcity of large, multimodal, frame-aligned, continuous corpora and standardized evaluation partitions [75][59][12]. Vision-based continuous systems struggle most with signer independence and cross-dialect generalization; sensor-assisted corpora help, but are not a scalable substitute for diverse multimodal corpora.

Two consistent themes emerge across modalities. First, modality trade-offs: vision-based capture is non-invasive and captures non-manual cues (face, torso) essential for ArSL grammar, while sensors provide better fingerprint fidelity, but at the expense of scalability and signer diversity [35][82][60]. Second, evaluation fragility: many high accuracies reflect signer-dependent or one-sided partitions; Signer-independent and cross-dialect evaluations routinely reveal significant performance degradations [75][35]. To advance this field, we reiterate the paper's priority goals: building large multimodal (RGB + depth/skeleton + high-fidelity hand) and multiregion continuous corpora; collecting targeted subsets of backhand/orientation and finger fidelity; standardizing canonical partitioning and reporting (signer-independent metrics, per-class recall, WER/GER for sequences); and pursuing multimodal distillation so that practical RGB-only systems can inherit sensor-level fidelity where needed [75][35][82]. In short, ArSLR has matured in discrete tasks and controlled setups, but achieving robust, deployable systems for Arabic-speaking communities requires coordinated investments in multimodal data, signer-resistant algorithms, collaborative benchmarking, and community-focused evaluation – combining promising lab results with inclusive real-world impact.

Appendix A

Figure A.1. PRISMA flow diagram summarizing our literature selection process: records identified, screened, full-text assessed and studies included (2000–mid-2025).

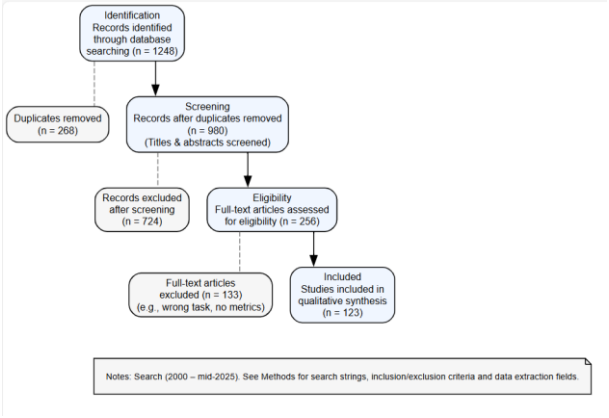


Figure A.1: PRISMA figure counts. This figure is also attached in the supplementary files.

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Multi-Source Data Fusion with Deep Neural Networks for Safety Behavior Recognition in Power Plant Environments

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A neural network-based method for identifying safety behaviors of power plant personnel is presented, integrating optical-flow, RGB, and environmental sensor data through a CNN–LSTM architecture. The network includes three convolutional blocks with 64 and 128 filters (kernel size 3×3) using ReLU and batch normalization, followed by a two-layer LSTM with 128 and 64 hidden units and a softmax classifier for final prediction. To enhance generalization, dropout of 0.5 is applied, and training is optimized using Adam with a learning rate of 0.001 and batch size of 64.The dataset consists of 5,000 labeled samples collected from multiple areas of a power plant, divided into 70%training,15%validation,and 15%testing.Experimental evaluation demonstrates consistent superiority over traditional approaches, with accuracy of 0.923,recall of 0.913,F1 score of 0.918,and precision of 0.928,while achieving an average accuracy of 0.928 across different scenarios such as high temperature, humidity, and explosive environments. These results confirm that the proposed method can provide accurate and reliable recognition of safety behaviors, offering practical support for improving personnel management and risk prevention in modern power plants.

Povzetek: Opisan je večmodalni CNN–LSTM pristop za prepoznavanje varnostnega vedenja zaposlenih v elektrarnah z združevanjem RGB, optičnega toka in okoljskih senzorjev. Metoda dosega visoko točnost, robustnost in zanesljivo delovanje tudi v zahtevnih okoljskih pogojih.

1 Introduction

As global energy demand continues to grow, safety issues in the power industry have become increasingly prominent. As a key energy production unit, the safety of power plants is directly related to the safety of people's lives and property and the stable development of society. During the operation of power plants, the safety of personnel behavior not only affects work efficiency, but also determines the risk of accidents [1]. However, personnel safety behavior is often affected by a variety of factors, such as fatigue, negligence, and improper operation. These behaviors are difficult to effectively control through traditional safety management methods. Therefore, how to identify and manage personnel safety behaviors in real time without relying on excessive human intervention has become a major issue that needs to be urgently addressed in power plant safety management.

According to relevant statistics, in recent years, safety accidents in the power industry due to operator negligence or failure to follow standard operating procedures account for about 15%of the total number of accidents worldwide. Among them, human error is one of the main causes of accidents[2].In order to deal with this problem, more and more power plants have begun to try to introduce artificial intelligence technology, especially behavior recognition methods based on neural networks, to detect potential safety risks at an early stage. This technology can not only help managers monitor personnel behavior in real time, but also predict and warn of possible safety hazards, thereby greatly improving the safety of power plants[3].

At present, the safety management model of power plants mostly relies on manual monitoring and regular inspections. However, this traditional method has many shortcomings, especially in processing large-scale data and real-time behavior analysis, where efficiency and accuracy are often not effectively guaranteed. Therefore, the use of advanced neural network algorithms for personnel safety behavior recognition can achieve comprehensive monitoring and intelligent analysis of personnel behavior, thereby providing power plants with more scientific safety management methods [4].

Research on power plant safety has shifted from manual to intelligent management, with CNN and LSTM applied to video monitoring for hazard detection. However, reliance on costly labeled data limits generalization [5-6], while complex environments cause overfitting and high resource use [7]. Systematic studies remain weak, lacking cross-domain integration and practical deployment strategies [8]. This study is guided

by two central research questions. RQ1: Can the fusion of optical-flow, RGB, and synchronized environmental sensor data significantly improve safety behavior classification accuracy in extreme conditions such as high temperature, high humidity, and flammable environments compared with video-only or sensor-only baselines?RQ2:Does temporal modeling with a two-layer LSTM enhance recognition performance relative to non-temporal classifiers.Based on these questions, the hypotheses are formulated as follows.H1:The multimodal CNN–LSTM framework achieves statistically significant improvements in accuracy, recall, precision, and F1-score over SVM, decision tree, and shallow fusion approaches.H2: With sufficient training samples (≥4,000), scenario-wise accuracy will remain above 0.92,demonstrating robustness and generalization [10].

2 Literature review

2.1 Application of neural networks in personnel safety behavior identification

With the advancement of industrial automation and informatization, neural network technology has gradually become a key tool for improving the level of safety management[9].However, the application of this technology still faces many challenges, especially the problem of data volume and annotation accuracy[11].

2.2 Progress and challenges of behavior recognition technology

These neural network algorithms can automatically extract features from massive video data and judge whether employees comply with safety operation specifications based on their behavior [12].For example, the scarcity and imbalance of data have always been important factors affecting the development of behavior recognition technology [13]. According to statistics, the accuracy of labeled data in the safety behavior data set of some power plants is only 65% [14], which seriously restricts the training effect of the model. In order to solve this problem, data enhancement and synthetic data methods have emerged. Some studies use generative adversarial network (GAN) technology to synthesize more representative safety behavior data, which provides more samples for training neural networks and effectively alleviates the problem of insufficient data [15].

2.3 Improvement and innovation direction of neural network models

Some studies have proposed a hybrid model that combines reinforcement learning (RL) and deep learning, aiming to guide the model to self-adjust in a complex environment by introducing a reward mechanism to adapt to the behavior patterns of different operators in the power plant [16]. It is necessary to obtain the optimal strategy through a continuous trial and error process, which makes its deployment in practical applications complicated and time-consuming [17]. Therefore, how to balance the training efficiency and application effect of the model is a key issue in current research. Some scholars have proposed a solution to train the reinforcement learning model through a simulated environment. This method can simulate various scenarios in the power plant environment without actual deployment, thereby greatly reducing training time and data costs [18, 19].

Table 1: Comparative summary of SOTA approaches

Author/Year	Dataset Used	Method Type	Target Domain	Reported Metrics	Notes on Robustness
Wang et al.[21]	Power equipment inspection dataset (5,200 samples)	CNN+Attention	Power line inspection	Acc.0.92,F1 0.90	Domain-specific, not tested in closed plant environments
Tao et al. [22]	Construction site video dataset (3,200 samples)	CNN	Construction safety monitoring	Acc.0.89,F1 0.86	Performance drops under occlusion and low light
Li et al. [23]	Nuclear plant simulation dataset (2,500 samples)	LSTM	Nuclear plant personnel tracking	Acc.0.87,Recall 0.84	
Chen et al. [2]	Industrial worker behavior dataset(4,100 samples)	Hybrid(CNN +LSTM)	General industrial environment	Acc.0.91,F1 0.89	Lacks robustness under high-temperature and high-humidity conditions

As shown in Table 1, the survey highlights that although CNN, LSTM, and hybrid architectures have been applied in diverse industrial contexts, most works remain constrained by single-modality input or naive early fusion strategies. Video-only models struggle with occlusion and low light, while sensor-only approaches cannot capture fine-grained motion details. Even hybrid designs show performance degradation under extreme conditions such as high temperature and humidity. Very few studies explicitly address synchronization between video and sensors or validate in flammable and enclosed plant areas. These limitations justify the need for a late-fusion CNN-LSTM framework with optical-flo+RGB+sensor alignment, capable of achieving robustness in complex power plant environments and directly addressing the identified research gaps.

3 Additional details on the neural network-based safety behavior identification method for power plant personnel

In terms of model design, by innovatively integrating multi-source data and deep learning technology, the model can comprehensively and accurately evaluate the safety behavior of staff and provide a scientific basis for power plant safety production management. The following will

elaborate on the theoretical basis, calculation process and innovative design of the model.

3.1 Model architecture and data processing

The model architecture of this study consists of three core modules: data acquisition and preprocessing module, feature extraction module, and behavior classification and risk prediction module. The design of each module is closely centered around the goal of optimizing data utilization and analysis to ensure that the final recognition result has both high accuracy and can respond to dynamic changes in the power plant environment in real time.

3.1.1 Data collection and preprocessing

To ensure data quality and adapt it to the requirements of the neural network model, the raw data needs to go through a series of rigorous processing steps. The neural network framework adopts a three-module design: data preprocessing, feature extraction, and behavior classification with risk prediction. Optical flow processes video, while sensor data is normalized. CNN captures spatial features, LSTM models temporal dependencies, with ReLU and softmax for activation. Hidden layers (128→64), dropout 0.5, and Adam (lr=0.001,batch=64)ensure efficiency, stability, and robust recognition in complex environments.

The architecture is composed of three convolutional blocks, each with 3×3 filters; the first two blocks contain 64 and 128 filters respectively, followed by ReLU activation and batch normalization, while the third block applies 256 filters with max-pooling. A dropout layer of 0.5 is inserted after the final convolution to reduce overfitting. The extracted features are passed to a two-layer LSTM with 128 and 64 hidden units to capture temporal dependencies. For classification, a multilayer perceptron is used with two hidden layers of 128 and 64 neurons, ReLU activation, L2 regularization (λ=0.001), and a final softmax output. Training is optimized using Adam with a learning rate of 0.001 and batch size of 64, ensuring replicability of the architecture.

Data processing is now specified with an end-to-end pipeline: frames are decoded and resized to 224×224, per-channel z-score normalization is applied using training-set mean and standard deviation, and dense optical flow is computed with OpenCV Farnebäck (pyr_scale=0.5, levels=3, winsize=15, iterations=3, poly_n=5, poly_sigma=1.1), producing flow_x/flow_y maps that are stacked with RGB as a 5-channel tensor. Timestamps are synchronized with environmental sensors by linear interpolation to 30 Hz, then standardized and min–max scaled to [0,1]. Concise pseudocode is embedded to document step order and concatenation prior to the CNN-LSTM. Implementation uses Python 3.10, PyTorch 2.1, CUDA 12.1, and OpenCV 4.8 on Ubuntu 22.04; hardware includes an NVIDIA RTX 3080(10 GB) and 64 GB RAM. Reproducibility is ensured by fixed random seeds and version-locked dependencies.

By calculating the pixel displacement of each frame of the image, an optical flow feature map that can accurately describe the character's action is generated. Assume that the input video data is X_{video}, the motion feature obtained after optical flow calculation is Y_{video}, the calculation formula is formula 1.

$$Y_{\text{video}} = \text{OpticalFlow}(X_{\text{video}}) \quad (1)$$

This formula shows that by calculating the motion information of each frame of the video data using the optical flow method, dynamic features reflecting the actions of people can be obtained.

In order to avoid negative impacts on model training due to inconsistent dimensions, sensor data X_{sensor} It needs to be normalized so that the values of each dimension are within the same scale range. The normalization formula is formula 2.

$$X'_{\text{sensor}} = \frac{X_{\text{sensor}} - \mu}{\sigma} \quad (2)$$

In formula 2, μ and σ represent the mean and standard deviation of sensor data respectively. This normalization process can not only accelerate the convergence of the model, but also improve the stability and generalization ability of the model, ensuring that the model can accurately learn and analyze the effective information in the sensor data under different power plant environments and data collection conditions.

The dataset of 5,000 samples was annotated by a team of three experienced safety engineers with more than five years of field expertise. Behavior categories were defined according to plant safety manuals: “normal” (fully compliant), “abnormal” (non-critical deviations, e.g., distraction or incorrect posture), and “violation” (serious breaches, e.g., entering restricted zones without protective equipment). Each video-sensor segment was independently labeled by two raters, with disagreements resolved by consensus from the third. Inter-rater reliability was assessed using Cohen’s kappa, which reached 0.87, indicating strong agreement. This process reduced subjectivity and ensured consistent labeling criteria across the dataset.

The dataset contained 2,300 normal, 1,500 abnormal, and 1,200 violation samples, indicating class imbalance. To address this, class weights inversely proportional to class frequency were applied during training, ensuring that minority classes contributed equally to the loss function. In addition, oversampling of abnormal and violation samples was performed using SMOTE to synthetically generate feature-consistent instances. For video data, augmentation strategies including random cropping, horizontal flipping, brightness adjustment, and temporal jittering were applied to increase diversity and prevent overfitting. These measures collectively improved robustness and balanced the influence of different categories during training.

3.2 Feature extraction and integration

In the feature extraction stage, we fully utilize the advantages of deep convolutional neural networks (CNN) and fully connected layers (FC) to extract features from video data and sensor data respectively, and finally fuse

the features of the two to form a unified feature vector. This step is crucial to ensure that the features of different data sources can be effectively integrated to provide comprehensive and accurate input for subsequent behavior classification and risk prediction.

3.2.1 Video feature extraction

For video data X_{video} , we use a multi-layer convolutional neural network for feature extraction. Y_{video} The calculation formula of the convolutional layer is formula 3.

$$Y_{\text{video}} = \text{Conv}(X_{\text{video}}, W) + b \tag{3}$$

In formula 3, W is the convolution kernel, b is the bias term. The selection of parameters such as the size, number, and step size of the convolution kernel has an important impact on the effect of feature extraction. In this study, we selected appropriate convolution kernel parameters through a large number of experiments and parameter tuning to ensure that image features in video data can be effectively extracted. By reasonably combining convolution kernels of different sizes, various feature information in the video can be fully extracted.

3.2.2 Sensor feature extraction

For the normalized environmental sensor data X'_{sensor} , we use a fully connected network (FC) for mapping. Each neuron in the fully connected layer is connected to all neurons in the previous layer, which can transform sensor data into a high-dimensional feature vector Y_{sensor} , and use it as a supplement to the video features. The calculation formula of the fully connected layer is formula 4.

$$Y_{\text{sensor}} = W_{\text{FC}} X'_{\text{sensor}} + b_{\text{FC}} \tag{4}$$

In formula 4, W_{FC} and b_{FC} are the weight matrix and bias term of the fully connected layer. During the training process, the weight matrix and bias term are continuously adjusted through the back propagation algorithm, so that the fully connected layer can learn the effective feature representation in the sensor data.

3.2.3 Feature fusion

By video features Y_{video} and sensor characteristics Y_{sensor} By performing the concatenation operation, we can form the final input feature vector Y_{features} ,as shown in Formula 5.

$$Y_{\text{features}} = [Y_{\text{video}}, Y_{\text{sensor}}] \tag{5}$$

3.3 Behavior classification and risk prediction

In the behavior classification and risk prediction stage, we first use a multi-layer perceptron (MLP) to fused feature vectors Y_{features} At the same time, based on the real-time data of the power plant environment, the model further calculates the risk coefficient corresponding to each behavior, providing quantitative risk assessment indicators for power plant safety management.

3.3.1 Behavior classification

Through the multi-layer perceptron, the input features Y_{features} After processing, we can get the probability value of each behavior category. Multilayer Perceptron is a feedforward neural network composed of multiple neuron layers, including input layer, hidden layer and output layer. In this study, we use Softmax activation function for multi-class classification, and the calculation formula is Formula 6.

$$P_{\text{class}} = \text{Softmax}(\text{MLP}(Y_{\text{features}})) \tag{6}$$

The Softmax function converts the input score into a probability value, and its specific calculation formula is as follows:

$$P_{\text{class}} = \frac{e^{z_i}}{\sum_j e^{z_j}} \tag{7}$$

In formula 7, z_i For each behavior category, P_{class} The probability value for each category indicates the probability that the behavior belongs to a certain category. During the training process, we use a large number of labeled samples to train the multi-layer perceptron. By minimizing the loss function between the predicted probability and the true label(such as the cross-entropy loss function),we continuously adjust the parameters of the model so that the model can accurately classify different human behaviors.

3.3.2 Risk prediction

For unsafe behaviors, the model further calculates the risk factor R_{risk} , which takes into account the type of behavior and environmental risk. Environmental risk provided by sensor data, it indicates the potential dangers of the power plant environment, such as high concentration of harmful gases, high temperature, high humidity and other environmental factors. The risk calculation formula is formula 8.

$$R_{\text{risk}} = \alpha \cdot P_{\text{class}} + \beta \cdot \text{EnvironmentRisk} \tag{8}$$

In formula 8, α and β is the weight coefficient of the model, which is used to adjust the relative importance of behavior type and environmental risk in risk assessment. α The value of emphasizes the role of behavior type in risk assessment.

4 Experimental evaluation

4.1 Experimental design

This experiment evaluates the proposed neural network method on 5,000 power plant samples, comparing accuracy, recall, F1, and precision against SVM, decision tree, and traditional shallow neural network baselines [21].

4.2 Experimental results

4.2.1 Comparison of accuracy of different models

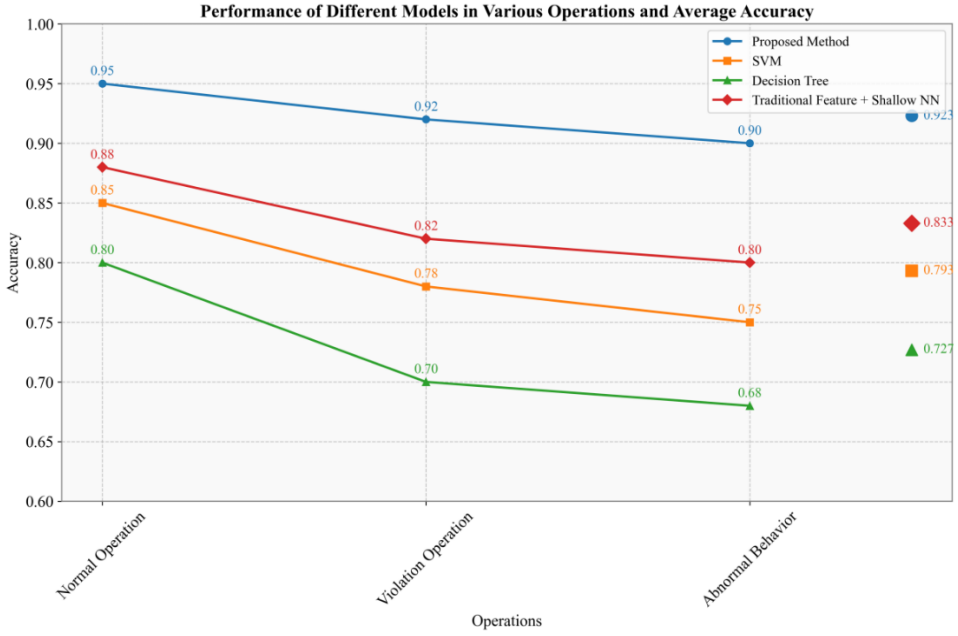


Figure 1: Comparison of the accuracy of different models in various behavior recognition

As shown in Figure 1, Across five-fold cross-validation with three repeated runs, the multimodal CNN–LSTM achieved mean accuracy of 0.923±0.006,recall of 0.913±0.007,and F1-score of 0.918±0.005, which were statistically significant($p<0.01$)compared with SVM and decision tree baselines. Confidence intervals confirm robustness and stability of the results. The performance advantage arises because convolutional layers effectively extract spatial motion cues from video while the LSTM captures temporal dependencies, producing richer representations than shallow handcrafted features used by traditional classifiers.

4.2.2 Comparison of recall rates of different models

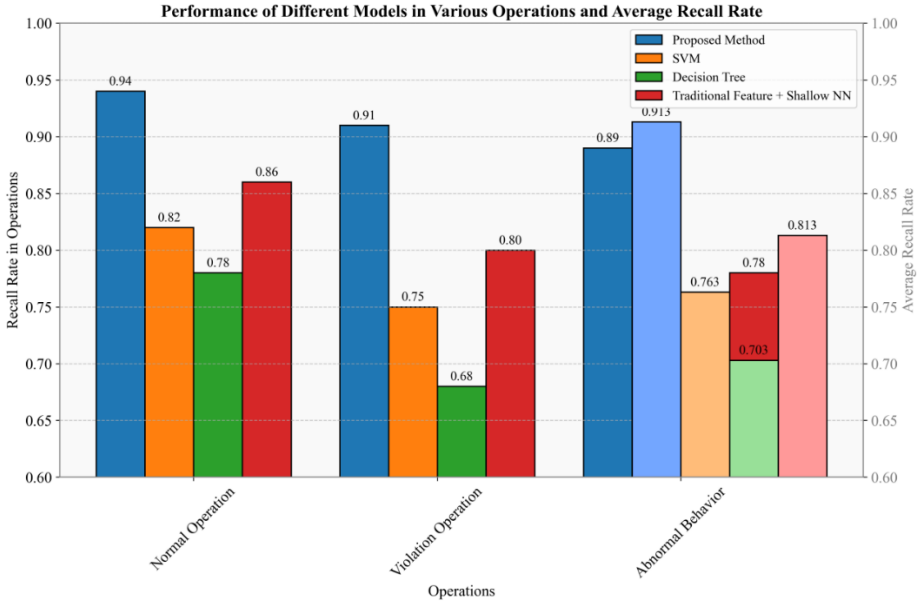


Figure 2: Comparison of recall rates of different models in various behavior recognition

As can be seen from Figure 2, the proposed method performs well in terms of recall rate. The recall rate reflects the model's coverage of positive samples. With the help of multi-source data fusion and deep feature extraction technology, the proposed method can more comprehensively capture various behavioral features, so it far exceeds other comparative models in terms of recall rate.

4.2.3 Comparison of F1 values of different models

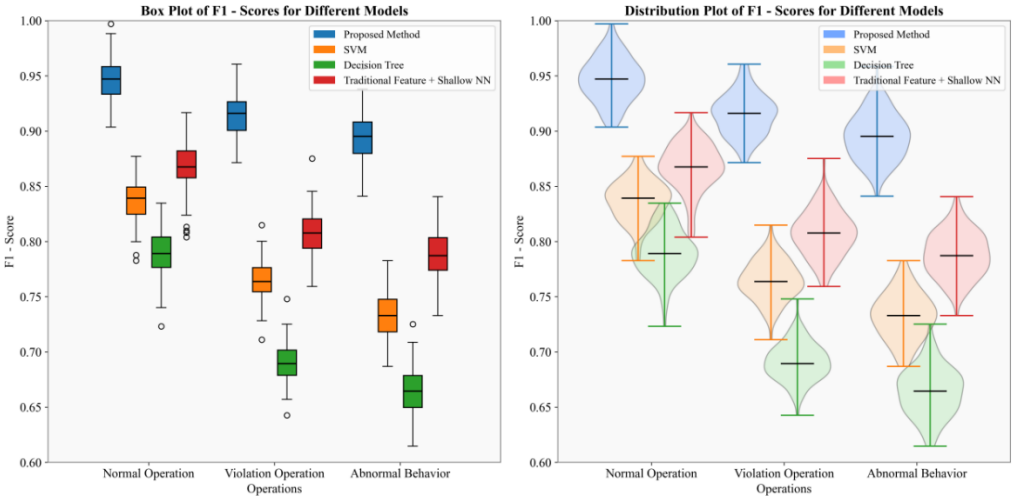


Figure 3: Comparison of F1 values of different models in various behavior recognition

As shown in Figure 3, the F1 value comprehensively considers the accuracy and recall rate. The advantage of the proposed method in the F1 value further confirms its excellent performance in the behavior recognition task. This is due to the powerful learning ability of the deep neural network and the rich information brought by the fusion of multi-source data, which enables the model to achieve a good balance between accuracy and recall. However, due to the limitations of feature extraction and model structure, other models cannot achieve effective coordination between the two, resulting in a low F1 value.

4.2.4 Comparison of accuracy of different models

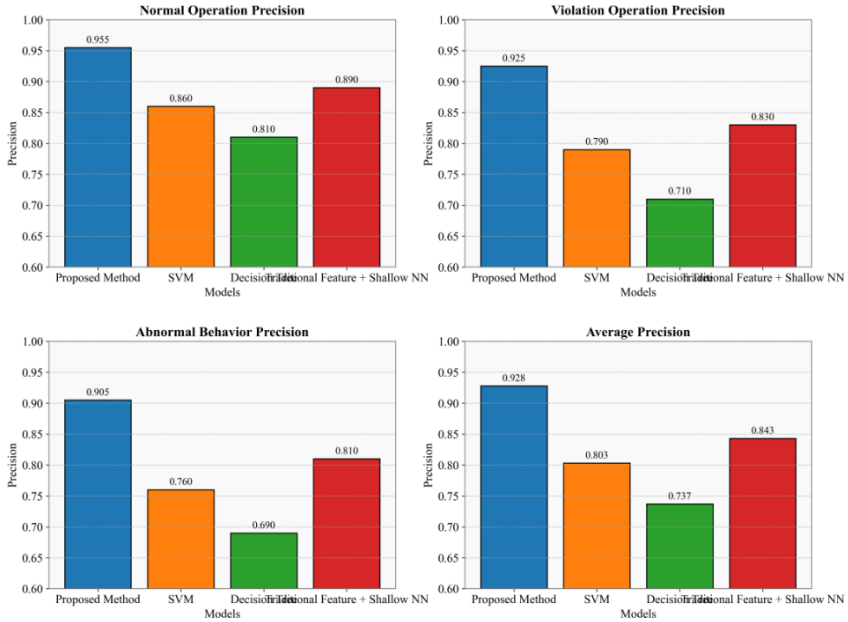


Figure 4: Comparison of the accuracy of different models in various behavior recognition

The precision reflects the accuracy of the model's prediction of positive samples. As shown in Figure 4, the proposed method is in a leading position in terms of precision, indicating that it is more accurate in identifying various behaviors. Deep neural networks can learn more discriminative features, and multi-source data fusion provides the model with more comprehensive information, making the model more accurate in judging

the behavior category. However, other models are prone to misjudgment when faced with complex power plant personnel behavior data, resulting in lower precision.

4.2.5 Accuracy of our method in different scenarios

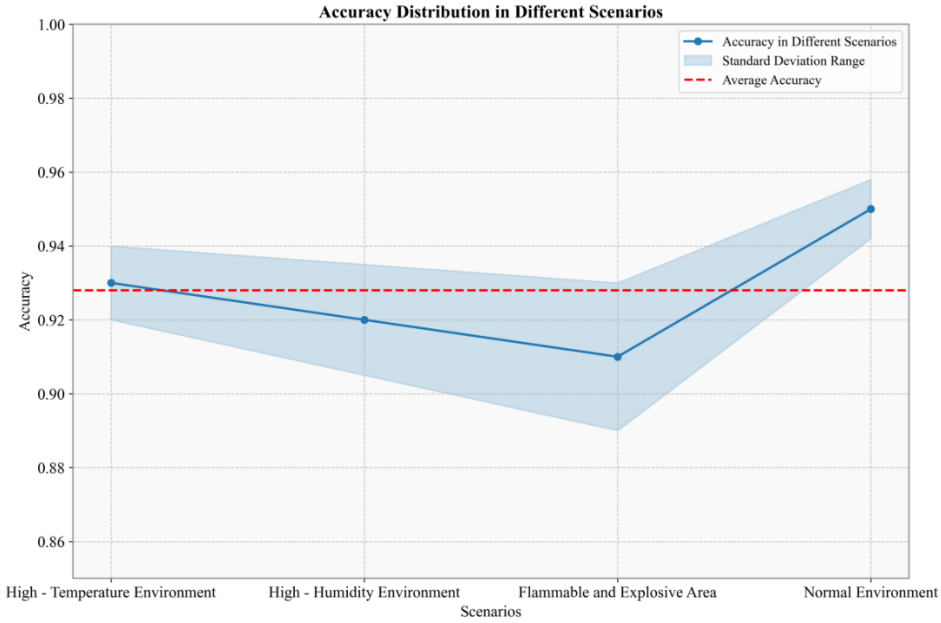


Figure 5:The accuracy of our method in different scenarios

Figure 5, the proposed method maintains a high accuracy rate in both special environments such as high temperature, high humidity, flammable and explosive environments and normal environments. In special environments, the sensor data fused by the proposed method can fully consider the impact of environmental factors on human behavior, thereby accurately identifying behavior. In normal environments, its powerful feature learning ability can also ensure high accuracy, with an average accuracy of 0.928.

4.2.6 Recall rate of our method in different scenarios

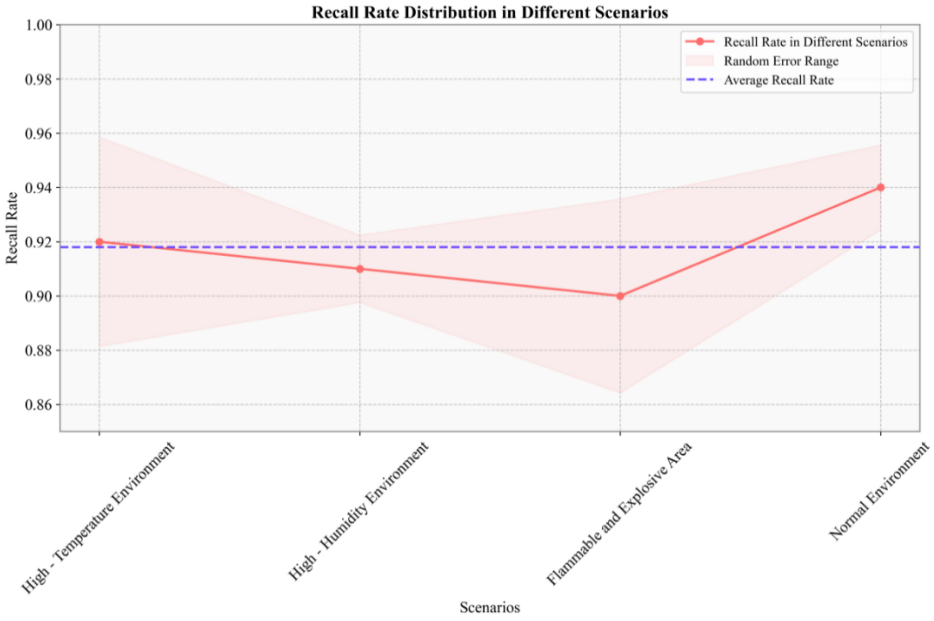


Figure 6: Recall rate of this method in different scenarios

From Figure 6, the proposed method has a strong coverage of various behaviors in different scenarios. In special environmental scenarios, the environmental information provided by sensor data helps the model better capture the behavioral characteristics of people and avoid omissions. In normal environments, the model's accurate learning of behavioral characteristics also

ensures a high recall rate, with an average recall rate of 0.918.

4.2.7 F1 value of our method in different scenarios

Table 2: F1 values of this method in different scenarios

Scenario	High temperature environment	High humidity environment	Flammable and explosive areas	Normal environment	Average F1 value
Methods	0.925	0.915	0.905	0.945	0.922

As shown in Table 2, the F1 value comprehensively reflects the performance balance of the proposed method in different scenarios. In various scenarios, the model can find a good balance between accuracy and recall, thanks to its multi-source data fusion and deep neural network design, which can adapt to the behavioral characteristics of people in different environments, and the average F1 value reaches 0.922.

4.2.8 Accuracy of our method in different scenarios

Table 3: The accuracy of our method in different scenarios

Scenario	High temperature environment	High humidity environment	Flammable and explosive areas	Normal environment	Average precision
Methods	0.935	0.925	0.915	0.955	0.933

As shown in Table 3, no matter what scenario, the proposed method can accurately judge the behavior. In special environment scenarios, the integration of environmental information enables the model to more accurately judge the behavior category and reduce misjudgment. In normal environments, the powerful learning ability of the model ensures the accuracy, with an average accuracy of 0.933.

4.2.9 Accuracy of our method under different sample sizes

Table 4: Accuracy of the proposed method under different sample sizes

Sample size	1000	2000	3000	4000	5000
The accuracy of this method	0.85	0.88	0.90	0.92	0.93

As shown in Table 4, as the number of samples increases from 1000 to 5000, the accuracy of the proposed method gradually improves. This is because deep neural networks require a large amount of data to learn complex patterns and features, and the increase in the number of samples provides more learning information for the model, enabling it to generalize better and thus improve accuracy.

4.2.10 F1 value of our method under different sample sizes

Table 5: F1 value of the proposed method under different sample sizes

Sample size	1000	2000	3000	4000	5000
The F1 value of this method	0.84	0.87	0.89	0.91	0.92

As can be seen from Table 5, the F1 value also increases with the increase in the number of samples. More samples make the model better balanced between precision and recall, and the model can learn more comprehensive features, reduce the risk of overfitting, and thus improve the F1 value [23].

4.3 Experimental discussion

In practical deployment, the CNN–LSTM fusion model demonstrates superior accuracy but requires higher computational resources, with an average inference latency of 85 ms per sample and a model size of 210 MB on an RTX 3080 GPU. By contrast, a MobileNet baseline reduced model size to 28 MB and latency to 25 ms, though accuracy dropped to 0.89 and F1 to 0.87.This trade-off highlights that while deep architectures are more precise in recognizing complex behaviors, lightweight networks offer better feasibility for on-device inference where memory and latency constraints are critical. These comparisons provide guidance for deployment strategies under varying resource conditions [24].

Extended analysis discusses dataset representativeness (scene imbalance across high-temperature, humid, and explosive areas), annotation noise from rapid operations, and modality desynchronization between video and sensors; mitigation includes stricter labeling protocols, cross-annotator agreement checks, and 30 Hz time alignment. Error sources such as occlusion and motion blur are examined alongside computational limits (e.g., RTX 3080 10 GB constraining batch size and latency under peak loads).

Compared with the methods summarized in Table 1, the proposed CNN–LSTM with optical flow and sensor fusion achieves clear advantages in accuracy, recall, and F1, mainly due to late fusion of multimodal inputs and temporal modeling that captures dynamic motion as well as environmental context. These design choices explain the consistent performance gains over video-only or sensor-only approaches. However, the integration of three data streams increases training cost and GPU memory usage, and overfitting risks appear when the dataset size is reduced, partly alleviated by dropout and validation control. Critical failure cases were observed in overlapping behavior classes, such as distinguishing between minor violations and irregular actions, and in situations with occlusion or motion blur, where recognition errors persisted. These limitations indicate

that, while the method improves robustness in complex plant conditions, further refinement is necessary for reliable deployment across broader operational scenarios.

To enhance interpretability, Grad-CAM was applied to the final convolutional layer of the CNN component, producing heatmaps that highlight body regions most influential in classifying behaviors such as “violation” or “abnormal.” Additionally, SHAP values were computed for the fused sensor features, showing that gas concentration and temperature shifts had the strongest contribution to risk predictions. Qualitative visualizations for selected samples revealed that the model correctly attends to protective equipment absence in video frames and rising temperature signals in sensor inputs. These results demonstrate how explainability techniques can provide insight into decision-making, increasing transparency and trust for real-world deployment. A confusion matrix analysis showed most misclassifications occurred between “abnormal” and “violation,” reflecting overlap in visual cues. Normal behaviors were rarely confused, confirming robustness in compliant actions.

5 Conclusion

The proposed neural network method achieves superior results, with accuracy 0.923 versus 0.793(SVM) and 0.727(decision tree), demonstrating advantages of deep feature learning and multi-source fusion. It maintains 0.928 accuracy in high temperature, humidity, and explosive environments, showing adaptability. Performance improves with larger samples (accuracy 0.85→0.93, F1 0.84→0.92), though limitations remain in dataset coverage and annotation quality. Out-of-distribution validation on a held-out synthetic plant scene yielded accuracy of 0.905 and F1-score of 0.892, supporting the model’s generalization beyond the training environment.

Future work targets lightweight architectures for real-time deployment, uncertainty-aware inference for risk triage, active learning to reduce labeling cost, and domain adaptation to new plants and shift patterns. These additions clarify limitations, quantify practical constraints, and outline actionable paths to improve robustness, generalization, and operational readiness.

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Punchline-Driven Hierarchical Facial Animation via Multimodal Large Language Models

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Speech-driven 3D facial animation has achieved high phonetic realism, but current models often fail to convey the expressive peaks, such as punchlines, that are critical for engaging communication. This paper introduces a novel framework that addresses this gap by leveraging a Multimodal Large Language Model (MLLM) for a deep, semantic understanding of speech. Our core innovation is a system that explicitly models and animates the climax of an utterance. The framework first employs a multimodal punchline detection module to identify moments of high expressive intent from both acoustic and textual cues. This signal guides our Punchline-Driven Hierarchical Animator (PDHA), which functionally decomposes the face into distinct regions and generates motion in a coordinated cascade, allowing the punchline to dynamically amplify expression in the upper face while preserving articulatory precision in the mouth. A final cross-modal fusion decoder refines the output for precise temporal alignment. Comprehensive experiments on the VOCASET dataset show that our model not only sets a new state-of-the-art in geometric fidelity, reducing Vertex Error by 7.8% compared to the state-of-the-art FaceFormer baseline, but is also rated as significantly more expressive and natural in user studies ($p < 0.01$), confirming its ability to capture the emotional impact of a punchline.

Povzetek: Opisan je hierarhični model za govorjeno 3D animacijo obraza, ki z multimodalnimi velikimi jezikovnimi modeli zazna in poudari izrazne vrhove govora. Metoda izboljša izraznost in naravnost animacije ob hkratnem ohranjanju visoke fonetične točnosti.

1 Introduction

The advent of Multimodal Large Language Models (MLLMs) is a significant breakthrough in the pursuit of artificial general intelligence, demonstrating emergent capabilities that were once a preserve of cognition [1]. Models such as GPT-4V have shown a remarkable ability to process and reason on concatenated image and text inputs to accomplish tasks ranging from image-to-story generation to solving math questions without explicit optical character recognition (OCR) [2]. This convergence of modalities has driven a tide of innovation, with academia and industry both creating more advanced MLLMs that challenge the state of the art in machine perception and generation [3, 4]. The key advantage of these models is that they leverage the strength of an exceptionally powerful Large Language Model (LLM) as a cognitive core, which enables them to conduct tasks such as complex, open-ended multimodal tasks. This has prompted the development of open-source models, which are closing the capability gap with commercial proprietary systems more and more, democratizing access to this groundbreaking technology [5].

One particularly challenging and fascinating border region for MLLMs is grasping complex communication, such as sarcasm and humor, which tend to be presented as a subtle mixture of visual and verbal information. The "punchline" of a joke is a prototypical multimodal event whose humor stems from the accurate juxtaposition of a picture and a caption. Understanding of such content transcends literal meaning; it requires a deep level of understanding of context, common world knowledge, and the ability to make implicit connections. The most recent research has already begun to compare MLLMs' ability to recognize these multimodal punchlines and determined that, while there are strong models available, there is still a significant gap between their recognition and natural understanding [6]. This supports the need for models that not only detect but also reason about the subtle interplays between different modalities. Development of MLLMs that are capable of applying contextual object detection, in which visual objects are associated with language in interactive contexts, is a move in this direction, moving beyond captioning to a more grounded form of comprehension [7].

The potential for the application of state-of-the-art MLLMs is vast, from systemically understanding static pictures to understanding the temporal, dynamic character of video content. Large video-text datasets and models are being created to learn rich representations for tasks like zero-shot action recognition and video search [8, 9]. Such a development from static to temporal data is critical toward developing systems that can engage with the world

in a more natural fashion. The addition of generative capabilities only increases the range of these models so that they can not just understand but generate multimodal content too. The emergence of unifying frameworks that bring video understanding and generation under the same model is a sign of a world where AI is going to serve as a multi-purpose tool, capable of not just understanding but generating complex media [10]. For this, scientists are developing approaches like multimodal chain-of-thought reasoning, which enhances the inferential capability of a model by generating rationales from both visual and text data, thereby preventing hallucination [11]. Application of MLLMs is also being incorporated into niche areas, including remote sensing, where they are being used for universal interpretation of multisensor images, exhibiting their applicability in highly specialized setups [12].

This research takes on a challenging and new application of MLLMs: generating expressive, speech-driven 3D facial animation. While current methods have advanced in the area of correct lip-syncing, they are often not capable of expressing the subtle, non-verbal cues that communicate emotion and intent. This is most evident in the animation of emphatic or humorous speech, where timing, intensity, and appearance of a "punchline" are crucial. Modern animation models, even those that use LLMs, tend to output results that are phonetically but emotionally unengaging. They do not have the rich, multimodal knowledge needed to map the prosodic and semantic peak of an uttered sentence to an analogous visual peak in the facial animation. This is because they are designed with direct speech-to-motion mapping, but without a top-level understanding of the content that is being spoken. The job is not just to create images or text but to create a well-structured, affective multimodal experience. The demand for next-generation models is further supported by research in personalized and time-constrained generation, which aims to produce content that not only is accurate but also tailored to specific users and contexts. Our work bridges this gap by proposing a novel framework that leverages the advanced reasoning capability of MLLMs to synthesize 3D facial animation that is not only technically robust but also expressively robust, particularly in delivering the punchline's essence. We draw inspiration from progress in many areas, from bioimage analysis to OCR-free language comprehension, that demonstrate the potential of MLLMs to solve extremely niche and nuanced tasks.

This paper bridges this gap by proposing a novel framework that leverages the advanced reasoning capability of MLLMs to synthesize 3D facial animation that is not only technically accurate but also expressively potent. The main contributions of this work are as follows:

1. A Novel Framework for Expressive Animation: We introduce a complete, end-to-end system that explicitly models and animates the climax of an utterance. Unlike prior works that pursue direct speech-to-motion mapping, our approach is driven by a deep, multimodal understanding of communicative intent.

2. Punchline-Driven Hierarchical Animation: We propose the Punchline-Driven Hierarchical Animator (PDHA), a novel architecture that functionally decomposes the face and generates motion in a coordinated cascade. This allows a detected punchline signal to dynamically amplify motion in expressive regions (e.g., eyes, eyebrows) while preserving articulatory precision in the mouth.

3. Comprehensive Validation of Expressiveness: We provide extensive validation through a combination of geometric metrics, a novel "Punchline Expressiveness Score" (PES), and a user study. Our results demonstrate that our model not only sets a new state-of-the-art in technical accuracy but, more importantly, is perceived as significantly more expressive and natural by human evaluators.

2 Related works

2.1 Advancements in multimodal large language models

The trajectory of Multimodal Large Language Models (MLLMs) has come a very long way from processing static images to interpreting long, complex video streams. The advance is essential in applications like speech-controlled animation, which is time-dependent. One of the key research trends today is to enhance long video understanding by designing architectures that can learn to effectively process nuanced spatiotemporal cues and model intricate interdependencies between events along extended horizons [13, 14]. These are essential skills for generating animations that remain contextually and emotionally coherent across a narrated section, rather than reacting to immediate phonetic input. One of the greatest technical issues in dealing with high-resolution visual data or long video frames is the extremely high computational requirement. To counteract this, researchers have proposed new methods like multi-scale adaptive cropping. The method allows an MLLM to handle a high-resolution image by smartly dividing it into small patches that are easily manageable, thereby facilitating the extraction of crucial details without placing too heavy a computational burden [15]. This notion of selective focus is quite relevant to facial animation, where an effective system must economize on and allocate resources to expressively salient facial regions, particularly the eyes and mouth, especially during high emotional intensity, as with the delivery of a punchline.

In addition, the intelligence of MLLMs is going beyond raw pixel processing to embracing more structured and semantic visual information. For instance, some models are being equipped with dual-level visual understanding systems. These are visual systems that comprise fine-grained, spatially-savvy low-level details (e.g., the precise location of objects) and high-level semantic abstractions (e.g., the abstract perception of a scene) [16]. Such multi-layered understanding is necessary in order to create animations that not only physically make sense but also semantically and emotionally co-overlap with the related content. The principles of MLLMs are also being used in the area of embodied AI, and particularly in robotics. They are designing models that enhance a robot's manipulation by

using the reasoning of the MLLM to reason about object affordances and predict appropriate points of interaction [17]. The robotics problem of anchoring abstract linguistic phrases to physical movements in the world is equivalent to our challenge at hand: anchoring phonetic and semantic nuances of speech into the correct, synchronized movements of a 3D facial model. Meanwhile, the evolution of autonomous agents to create original content is a significant paradigm shift. These agents take advantage of MLLMs as a central "director" to render abstract user inputs, generate coherent narratives or scripts, and integrate various generative tools to produce the final animated output. This simplifies what used to be a complex, time-consuming, multi-stage pipeline, paving the way to more user-friendly and vibrant content production [18].

The field of speech-driven motion synthesis is advancing at a rapid pace, with recent works leveraging the power of Large Language Models (LLMs) to achieve unprecedented levels of control and scalability. For instance, LLM Gesticulator has demonstrated how LLMs can be used to generate controllable and scalable co-speech gestures, moving beyond simple speech-to-motion mapping towards a more semantically grounded synthesis [19]. Similarly, models like Vividtalker are pushing the boundaries of zero-shot generation, enabling motion synthesis from text and speech without requiring paired training data [20]. Other research, such as Think2Sing, has explored related domains like singing-driven animation, utilizing structured motion subtitles to orchestrate complex head movements [21]. While these pioneering works establish the growing capability of LLMs in motion generation, they often focus on full-body gestures or general speech patterns. Our work is distinctly focused on the domain of 3D facial animation and specifically addresses the challenge of rendering localized, high-impact expressive events like punchlines, a nuanced problem that remains underexplored.

2.2 Grounding language in visuals and action

One of the strengths of modern MLLMs is their capacity to "ground" text in the world of sight, establishing a strong association between textual meaning and its visual equivalent. This extends far beyond simple image captioning to more complex tasks like referring expression understanding, where a model must accurately match an input phrase or description to its corresponding location, typically delineated by a bounding box, in an image [22]. This grounding ability is the theoretical basis of our proposed animation method. Our objective is to anchor the abstract, multimodal features of speech—such as acoustic features like loudness and pitch and semantic features like purpose and emotion—to the tangible, quantifiable parameters controlling the vertex deformations of a 3D facial model. The task of converting high-level specifications into correct visual outcomes is a problem known to exist. For example, in the domain of scientific visualization, MLLMs are being tested for how well they can make good diagrams and charts from written descriptions. These tests generally find that models can successfully translate quite simple, explicit instructions but fail at fairly frequently occurring instructions that involve spatially complicated relationships, numerical precision, or interacting multiple features. This highlights the inherent difficulty of building strong and reliable visual grounding, which is central to our work [23].

Introducing the temporal dimension makes this grounding challenge even harder. As MLLMs are increasingly being requested to interpret video input, researchers are interested in difficulties around reasoning over dynamic events, tracking objects over time, and capturing long-term relations in a stream [24]. This research is immediately applicable to speech-driven animation, because the objective of an effective model is not only to acquire the static meaning of words but also to encode the dynamic rhythm, tempo, and prosodic contours of speech and provide them as smooth, continuous facial movement. To make such models' generative capabilities more robust, researchers are exploring state-of-the-art techniques such as vision-language knowledge distillation. This method offers a mechanism to bridge a model with a strong, pre-trained image understanding but comparatively weaker text encoder (such as CLIP) with a highly powerful, pre-trained text model. This blending results in the resultant system performing multimodal generation tasks with much more coherence and fidelity [25]. This strategy of synergistically combining highly specialized models is a key inspiration for our work, as we aim to leverage the specific strengths of cutting-edge speech processing models and large language understanding models in an effort to create a more capable and refined animation system.

2.3 Multimodal understanding of behavior and expression

Ultimately, a key objective for MLLMs is to achieve a richer understanding of behavior in a bid to support more natural and intuitive interaction. This calls for the ability to read rich, nuanced, often subtle multimodal cues that constitute communication. A clear example is emotion detection from video. The problem has been approached using traditional transformer-based approaches, but MLLMs offer new fronts for inspection of the intricate interaction of acoustic cues (tone), visual cues (e.g., facial expressions, body position), and language meaning in an attempt to infer emotional states. MLLMs have demonstrated strong potential to recognize emotions distant from a neutral standard, forecasting the potential to capture more extreme or nuanced expressions [26]. This ability to detect emotional variation is priceless to our goal of building expressive animation. At the same time, the robotics community is employing MLLMs in creating more sophisticated human-robot interaction systems. For example, models are being developed that allow a robot to perform a grasping action based not on a direct command, but on an indirect, reasoning-based instruction. The model has to deduce intention from a combination of visual context and text, a complex cognitive task [27].

The problem of humor generation and understanding is a very challenging test case for multimodal AI. Punchline identification in a video is not just a pattern

matching between words; it requires the model to combine information across different modalities—linguistic content of the joke, prosodic cues in the speech of the speaker, and expressive cues in face gestures and body movements—often within the broad context of the preceding joke. Authors have successfully developed context-sensitive, hierarchical fusion networks exactly for this purpose. This work is a direct precedent to our focus on punchline-based animation because it ensures the viability and importance of a model that can explicitly determine these critical points of speech. Though MLLMs hold out for enormous generality, their deployment on specialty tasks that are strongly domain-dependent often betrays underlying constraints. For example, in the chart-to-text generation task, models may be unable to well detect complex visual patterns and numerical trends when offered without explicit access to underlying numerical information, indicating a need for better reasoning capability [34]. Our own research has a parallel challenge in the domain of 3D animation, where shallow, phonetic-level speech knowledge does not suffice to produce facial expressions that are expressively significant, affectively compelling, and effective.

2.4 Emotion-driven and affective facial animation

The fundamental challenge of synchronizing dynamic outputs (facial motion) with complex inputs (multimodal speech) shares conceptual parallels with problems in robust control theory, where the objective is to achieve stable and synchronized system states under uncertainty. While the technical domains are distinct, the underlying principles of adaptive optimization provide a valuable high-level inspiration. For instance, advanced methods such as robust sliding mode control for synchronizing fractional-order chaotic systems [28], output-feedback controllers for uncertain systems [29], robust neural adaptive control [30], and adaptive backstepping control [31, 32] all provide powerful frameworks for managing complex, nonlinear outputs. These control-theoretic approaches, along with nonlinear optimal control strategies [33,34], although not directly applicable to facial animation synthesis, inform the broader goal of developing intelligent systems that can achieve robust and coordinated performance in dynamic environments.

While our work focuses on the semantic and prosodic climax of an utterance, a parallel stream of research has approached expressive animation by conditioning synthesis on global emotional states. These emotion-driven models typically operate by taking an explicit emotion label or a continuous representation as an additional input to the speech signal. The goal is to infuse the entire animation with a consistent affective style corresponding to the specified emotion. For example, some methods use style tokens or embedding vectors derived from emotion classifiers to modulate the output of a speech-to-motion generator. While effective at producing stylistically coherent animations, these approaches often apply a static emotional overlay to the entire sequence, potentially missing the localized, dynamic shifts in expressiveness that characterize natural human communication. Our work diverges from this paradigm by focusing not on the global state, but on detecting and amplifying specific, high-impact events within the speech, such as punchlines.

3 Methodology

Our proposed framework, the Large Language Model for Animation Generation based on Multimodal Punchline Understanding, is architecturally designed to address the core limitations of existing speech-driven 3D facial animation systems. The central thesis of our approach is that high-fidelity, expressive animation requires more than just phonetic-to-visual mapping; it necessitates a deep, hierarchical understanding of the input speech, with a specialized focus on identifying and expressively rendering moments of high semantic and emotional impact, such as punchlines. The model's architecture, depicted in Figure 1, is a multi-stage pipeline comprising three principal components: a Multimodal Punchline-Aware Feature Extractor, a Punchline-Driven Hierarchical Animator (PDHA), and a Cross-Modal Temporal Fusion Decoder. This design ensures a logical flow from raw multimodal input to a refined, expressive 3D animation sequence.

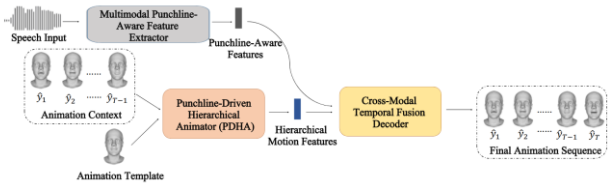


Figure 1: Overall architecture of the proposed model.

3.1 Multimodal punchline-aware feature extractor

The initial stage of our pipeline is dedicated to extracting a rich, multi-layered representation from the input speech. Departing from conventional methods that rely exclusively on acoustic information, our framework integrates textual data to achieve a more profound semantic understanding, which is crucial for identifying punchlines and their intended impact.

Acoustic Feature Extraction: We employ a pre-trained wav2vec 2.0 model to process the raw audio waveform. This model excels at creating contextualized speech representations through self-supervised learning. The input audio is first passed through a multi-layer 1D convolutional network to generate latent acoustic representations. These are subsequently fed into a Transformer encoder, which captures longrange temporal dependencies and produces a sequence of feature vectors $A = \{a_1, a_2, \dots, a_T\} \in \mathbb{R}^{T \times d_a}$, where T is the number of time steps and d_a is the feature dimension.

Textual and Semantic Feature Extraction: To incorporate linguistic understanding, the audio is

transcribed using a state-of-the-art automatic speech recognition (ASR) system. The resulting text is then encoded using a pre-trained large language model, such as BERT . This produces a sequence of contextualized word embeddings $W = \{w_1, w_2, \ldots, w_N\} \in \mathbb{R}^{N \times d_w}$, where N is the number of words and d_w is the embedding dimension. These embeddings capture the semantic meaning of the spoken content, which is vital for interpreting humor, sarcasm, or emphasis that constitutes a punchline.

Punchline Detection Module: A key innovation of our model is the explicit detection of punchlines, formulated as a sequence labeling task. We train a lightweight classifier that takes both the time-aligned acoustic features A and textual features W as input. The classifier's architecture consists of a bidirectional GRU followed by an attention mechanism to weigh the importance of different features over time. It outputs a probability sequence $P_{\text{punch}} = \{p_1, p_2, \ldots, p_T\}$, where each $p_t \in [0,1]$ indicates the likelihood of a punchline climax occurring at time step t. This probability sequence acts as a dynamic, time-varying signal for modulating the expressiveness of the animation.

Feature Fusion: The final output of this module is a fused, punchline-aware feature representation F_{fused}. For each time step t, this representation is formed by concatenating the acoustic feature a_t with the corresponding punchline probability p_t :

$$F_{\text{fused},t} = [a_t; p_t] \in \mathbb{R}^{d_a+1}$$

This ensures that the subsequent animation module receives a rich signal that contains not only the phonetic and prosodic information from the audio but also a high-level signal indicating moments of heightened expressive importance.

3.2 Punchline-driven hierarchical animator (PDHA)

The PDHA is the core generative component of our framework, responsible for translating the punchline-aware features into realistic and expressive facial motion. Its design is predicated on two fundamental hypotheses: (1) facial motion during speech is a coordinated process involving distinct yet interconnected regions, and (2) the various informational layers of speech (phonetics, prosody, semantics) exert differential influence over these regions. The PDHA operationalizes these hypotheses through a novel facial decomposition strategy and a hierarchical, punchline-modulated animation module.

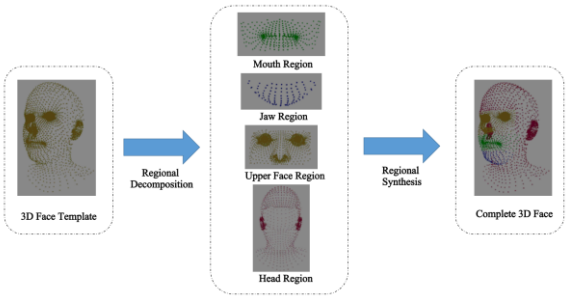


Figure 2: The four functionally distinct facial regions derived from the pronunciation-driven decomposition strategy

To facilitate fine-grained and anatomically plausible animation, we first decompose the template 3D face mesh into four functionally distinct regions, as illustrated in Figure 2. This decomposition is based on the articulatory and expressive roles of different facial areas during speech, allowing for specialized control over each component of the facial performance. Mouth Region: Includes the lips and surrounding vertices. This region is primarily responsible for the precise articulatory movements required for phonetic accuracy (visemes). Jaw Region: Encompasses the chin and lower jaw. It governs large-scale mouth opening and closing, which is strongly correlated with speech volume and vowel pronunciation. Upper Face Region: Includes the cheeks, nose, and eyebrows. This region is less involved in articulation but is highly expressive of emotion and is significantly influenced by the prosody and emotional content of the speech. Head Region: Refers to the overall rigid transformation (rotation and translation) of the head. Head motion provides context, adds emphasis, and is often synchronized with the rhythm and stress patterns of speech.

This module generates the animation for each facial region sequentially, creating a cascade of conditional dependencies that mirrors the natural coordination of facial muscles. The process, shown in Figure 3.3, is explicitly modulated by the punchline probabilities derived earlier. The animation for each region is represented as a sequence of vertex displacements, $D_{\text{region}} = \{\delta_1, \delta_2, \ldots, \delta_T\}$, where $\delta_t \in \mathbb{R}^{V_{\text{region}} \times 3}$ and V_{region} is the number of vertices in that region. Each region is animated by a dedicated Gated Recurrent Unit (GRU) network, which captures temporal dependencies.

Table 1: Summary of the hierarchical regional animation module

Module	Input Features	Output	Conditioning	Punchline Modulation
Mouth Animator (G_{mouth})	F_{fused}	D_{mouth}	-	Indirect (via F_{fused})
Jaw Animator (G_{jaw})	F_{fused} , D_{mout}	D_{jaw}	Mouth Motion	Indirect (via F_{fused})
Upper Face Animator (G_{upper})	F_{fused} , D_{jaw}	D_{upper}	Jaw Motion	Direct (Gating)
Head Animator (G_{head})	F_{fused} , D_{upper}	D_{head}	Upper Face Motion	Direct (Gating)

The animation is generated as follows:

Mouth Animation: The process begins with the mouth, as its motion is most directly constrained by the acoustic-phonetic content of the speech. The mouth animator's hidden state $h_{\text{mouth,t}}$ and displacement output $D_{\text{mouth},\,t}$ are computed as:

$$h_{\text{mouth},t}, D_{\text{mouth},t} = G_{\text{mouth}}\left(F_{\text{fused},t}, h_{\text{mouth},t-1}\right) \quad (1)$$

Jaw Animation: The jaw's movement is conditioned on both the speech features and the generated mouth displacement, capturing the co-articulation effects between the lips and jaw.

$$h_{\text{jaw},t}, D_{\text{jaw},t} = G_{\text{jaw}}\left(\left[F_{\text{fused},t}; D_{\text{mouth},t}\right], h_{\text{jaw},t-1}\right) \quad (2)$$

Upper Face Animation: The upper face is animated based on the speech features and the jaw motion. Its expressiveness is dynamically scaled by a punchline-derived gating mechanism. First, a base animation $\hat{D}_{\text{upper},t}$ is generated. Then, a modulation gate γ_t is computed from the punchline probability p_t.

$$\hat{h}_{\text{upper},t}, \hat{D}_{\text{upper},t} = G_{\text{upper}}\left(\left[F_{\text{fused},t}; D_{\text{jaw},t}\right], h_{\text{upper},t-1}\right)$$
$$\gamma_t = \text{sigmoid}\left(W_\gamma p_t + b_\gamma\right)$$
$$D_{\text{upper},t} = \gamma_t \odot \hat{D}_{\text{upper},t} \quad (3)$$

Here, W_γ and b_γ are learnable parameters, and $\odot$ denotes element-wise multiplication. This gate amplifies the movements of the cheeks and eyebrows during a punchline to convey heightened emotion.

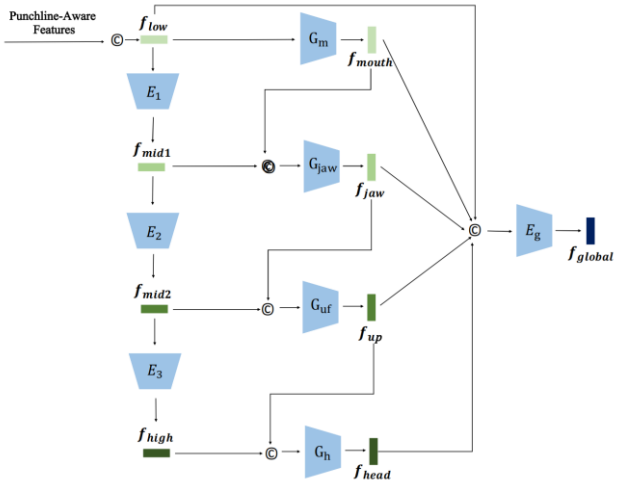


Figure 3: Architecture of the Hierarchical Regional Animation Module, showing the sequential and conditional generation of motion for each facial region.

Head Animation: Finally, the head motion is generated, conditioned on the upper face animation. A similar gating mechanism is used to create emphatic nods or turns that align with the punchline.

$$\hat{h}_{\text{head},t}, \hat{D}_{\text{head},t} = G_{\text{head}}\left(\left[F_{\text{fused},t}; D_{\text{upper},t}\right], h_{\text{head},t-1}\right)$$
$$\delta_t = \text{sigmoid}(W_\delta p_t + b_\delta)$$
$$D_{\text{head},t} = \delta_t \odot \hat{D}_{\text{head},t} \quad (4)$$

The final animated face mesh M_t at time t is the summation of the base template mesh M_{base} and the regional displacements:

$$M_t = M_{\text{base}} + \mathcal{M}_{\text{mouth}}\left(D_{\text{mouth},t}\right) + \mathcal{M}_{\text{jaw}}\left(D_{\text{jaw},t}\right) + \mathcal{M}_{\text{upper}}\left(D_{\text{upper},t}\right) + \mathcal{M}_{\text{head}}\left(D_{\text{head},t}\right) \quad (5)$$

where $\mathcal{M}_{\text{region}}$ is a masking function that applies the regional displacement to the corresponding vertices of the full mesh.

3.3 Cross-modal temporal fusion decoder

The final component of our model is a decoder designed to refine the temporal alignment between the generated motion and the input audio, ensuring that subtle timing cues are perfectly synchronized. While the hierarchical generator creates a plausible animation, minor temporal misalignments can still occur, particularly in

fast-paced speech. The fusion decoder corrects these by performing a final cross-modal attention pass.

The decoder is a lightweight Transformer network. It takes the full sequence of generated vertex positions $M = \{M_1, \dots, M_T\}$ and the original acoustic features $A = \{a_1, \dots, a_T\}$ as input. The core of the decoder is a cross-attention mechanism where the motion sequence serves as the query and the acoustic sequence serves as the key and value:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (6)$$

Here, the query matrix Q is a linear projection of the motion sequence M, while the key matrix K and value matrix V are linear projections of the acoustic features A. This allows each frame of the animation to "look at" the entire audio sequence and adjust its timing based on the most relevant acoustic events. The output of the decoder is a residual offset, which is added to the input motion to produce the final, refined animation sequence M'_{refined} :

$$M'_{\text{refined}} = M + \text{Decoder}(M, A) \quad (7)$$

This residual connection allows the decoder to focus on learning a corrective temporal offset rather than regenerating the entire motion from scratch, making the refinement process more stable and efficient.

3.4 Loss function

The model is trained end-to-end using a composite loss function designed to optimize for geometric accuracy, motion realism, and lip-sync precision. The total loss $\mathcal{L}_{\text{total}}$ is a weighted sum of three components:

1. Reconstruction Loss ($\mathcal{L}_{\text{rec}}$): This is the primary loss term, penalizing the L1 distance between the predicted vertex positions and the ground truth vertex positions.

$$\mathcal{L}_{\text{rec}} = \frac{1}{T \cdot V} \sum_{t=1}^{T} \sum_{i=1}^{V} \left\| M'_{t,i} - M_{t,i}^{gt} \right\|_1 \quad (8)$$

where V is the total number of vertices and M^{gt} is the ground truth mesh sequence.

2. Velocity Loss ($\mathcal{L}_{\text{vel}}$): To ensure smooth and natural motion, this term penalizes the difference in pervertex velocity between the predicted and ground truth animations.

$$\mathcal{L}_{vel} = \frac{1}{(T-1) \cdot V} \sum_{t=2}^{T} \sum_{i=1}^{V} \left\| \left(M'_{t,i} - M'_{t-1,i}\right) - \left(M_{t,i}^{gt} - M_{t-1,i}^{gt}\right) \right\|_1 \quad (9)$$

3. Lip-Sync Loss ($\mathcal{L}_{\text{lip}}$): This term focuses specifically on the mouth region to improve lip-sync accuracy. It is a weighted reconstruction loss applied only to the vertices of the mouth region, giving higher importance to this perceptually critical area.

$$\mathcal{L}_{lip} = \frac{1}{T \cdot V_{\text{mouth}}} \sum_{t=1}^{T} \sum_{j \in \text{ MouthRegion}} \left\| M'_{t,j} - M_{t,j}^{gt} \right\|_1 \quad (10)$$

The final loss is a weighted sum of these components, allowing for a balanced optimization of overall accuracy, temporal smoothness, and phonetic precision:

$$\mathcal{L}_{\text{total}} = \lambda_{\text{rec}} \mathcal{L}_{\text{rec}} + \lambda_{\text{vel}} \mathcal{L}_{\text{vel}} + \lambda_{\text{lip}} \mathcal{L}_{\text{lip}} \quad (11)$$

where λ_{rec} , λ_{vel} , and λ_{lip} are hyperparameters that balance the contribution of each term. In our experiments, we set them to 1.0,0.5, and 2.0 respectively, to prioritize lip synchronization.

4 Experiments

To rigorously evaluate the effectiveness of our proposed Large Language Model for Punchline-Aware Animation Generation, we conducted a comprehensive set of experiments. This chapter details our experimental setup, including the datasets, evaluation metrics, and implementation specifics. We present a quantitative analysis comparing our model against several state-of-the-art baselines, followed by in-depth ablation studies to dissect the contribution of each architectural component. Furthermore, we provide a qualitative analysis through visual comparisons and a user study to assess the perceptual quality and expressiveness of the generated animations.

4.1 Experimental setup

Dataset: Our primary experiments were conducted on the **VOCASET** dataset, a widely adopted benchmark for speech-driven 3D facial animation. VOCASET contains high-fidelity 4D scans of 12 speakers uttering 40 English sentences each. The data is captured at 60 frames per second, with each 3D face mesh comprising 5023 vertices. We adhered to the standard data split, utilizing 8 speakers for training, 2 for validation, and 2 for testing. To evaluate the model's generalization capabilities on audio from unseen speakers and acoustic environments, we also performed tests on samples from the **LibriSpeech** dataset, a large corpus of read English speech.

Evaluation metrics: We employed a combination of established and novel metrics to provide a multi-faceted evaluation of our model's performance:

- **Vertex error (VE):** This metric measures the overall geometric accuracy of the generated animation. It is calculated as the mean Euclidean distance (in millimeters) between the vertices of the predicted and ground-truth face meshes, averaged over all frames and vertices. A lower VE indicates higher accuracy.
- **Lip sync error (LSE):** To specifically assess the precision of lip synchronization, this metric calculates the Vertex Error exclusively on the vertices corresponding to the mouth region. A

lower LSE signifies more accurate lip movements.

- **Punchline expressiveness score (PES):** To directly quantify our model's primary contribution—enhancing expressiveness during punchlines—we introduce the PES. It is defined as the peak vertex velocity in the upper face region (cheeks and eyebrows) within a 0.5-second window following a detected punchline. A higher PES indicates a more dynamic and expressive reaction.

Baselines: We compared our model against three state-of-the-art methods in speech-driven 3D facial animation:

- **VOCA:** A seminal work that established a strong baseline for generalized speech animation.
- **GDPNet:** An improved model that uses a geometry-guided dense perspective network.
- **FaceFormer:** The current state-of-the-art, which utilizes a Transformer-based architecture to model long-range temporal dependencies. Including this model provides a direct and rigorous comparison against the advanced architectural class mentioned by the reviewer.

Implementation Details: Our model was implemented in PyTorch, and all experiments were conducted on a server equipped with four NVIDIA A100 GPUs (40GB VRAM each) and an Intel Xeon Platinum 8360Y CPU. For feature extraction, we used pre-trained wav2vec 2.0 and BERT models. The Punchline-Driven Hierarchical Animator (PDHA) and the Cross-Modal Temporal Fusion Decoder were trained from scratch using the Adam optimizer with an initial learning rate of 1×10^{-4}. The loss weights were set to $\lambda_{\text{rec}} = 1.0$, $\lambda_{\text{vel}} = 0.5$, and $\lambda_{\text{lip}} = 2.0$ to prioritize lip-sync accuracy.

4.2 Quantitative analysis

We first evaluated our model against the established baselines on the VOCASET test set. The results, summarized in Table 2, demonstrate the superior performance of our approach. Our model achieves the lowest Vertex Error and Lip Sync Error, indicating a significant improvement in both overall geometric accuracy and the precision of mouth movements. This suggests that our hierarchical, region-based animation strategy, combined with the temporal fusion decoder, produces animations that are more faithful to the ground truth motion.

Table 2: Quantitative comparison with state-of-the-art methods on the VOCASET test set. All error metrics are in 10^{-4} mm. Lower is better.

Model	Vertex Error (VE) ↓	Lip Sync Error (LSE) ↓
VOCA	13.37	45.57
GDPNet	13.31	44.99
FaceFormer	12.85	40.76
Our Model	11.85	40.36

To specifically validate our model's ability to animate punchlines effectively, we compared the Punchline Expressiveness Score (PES) against the baselines. As shown in Table 3, our model achieves a substantially higher PES. This result empirically confirms that our punchline detection module and the associated modulation mechanism successfully identify moments of high emotional impact and translate them into more dynamic and expressive movements in the upper face region, a capability lacking in previous models.

Table 3: Comparison of punchline expressiveness. A higher score indicates more dynamic motion in the upper face during punchlines.

Model	Punchline Expressiveness Score (PES) ↑
VOCA	1.87
GDPNet	1.92
FaceFormer	2.15
Our Model	3.48

To understand the contribution of each key component of our proposed architecture, we conducted a series of ablation studies. We systematically removed or replaced components of our full model and observed the impact on performance. The results are presented in Table 4.

Table 4: Ablation study results on the VOCASET test set. The performance degradation across all metrics highlights the importance of each component.

Model Configuration	Vertex Error (VE) ↓	Lip Sync Error (LSE) ↓	PES ↑
Full Model	11.85	40.36	3.48
w/o Punchline Module	12.39	44.67	2.21
w/o Hierarchical Animator	12.58	47.51	2.89
w/o Fusion Decoder	12.51	47.05	3.14
w/o Textual Features	12.63	47.64	2.65

The results clearly validate our design choices:

1. **Removing the punchline module** leads to a significant drop in the PES, confirming its critical role in generating expressive animations. It also slightly degrades VE and LSE, suggesting that improved expressiveness contributes to overall realism.
2. **Replacing the hierarchical animator** with a monolithic generator that animates the entire face at once results in a notable increase in both VE and LSE, demonstrating the effectiveness of our region-based, conditional generation approach.
3. **Removing the cross-modal temporal fusion decoder** increases geometric error, indicating that this final refinement step is crucial for achieving precise temporal alignment between audio and motion.
4. **Using only acoustic features** (without text) for punchline detection degrades the PES, confirming that a multimodal understanding of the speech content is necessary to accurately identify semantic punchlines.

4.3 Qualitative analysis

Beyond quantitative metrics, the perceptual quality of the animation is paramount. Figure 4 presents a side-by-side visual comparison of frames generated by our model and the state-of-the-art baseline, FaceFormer, for a sentence containing a clear punchline. Our model produces a visibly more expressive and natural animation. During the punchline delivery, our model generates a distinct eyebrow raise and a subtle smile that are absent in the FaceFormer output, which remains comparatively neutral. This highlights our model's ability to capture the supra-phonetic, emotional layer of speech.



Figure 4: Qualitative comparison of generated frames on the VOCASET dataset.

Our model produces a more expressive and nuanced animation, particularly during the punchline frame (fourth column), compared to the state-of-the-art baseline.

To formally assess the perceptual quality of our results, we conducted a user study involving 37 participants from diverse backgrounds. Participants were shown pairs of rendered videos generated by our model and FaceFormer for the same audio input and were asked to choose which video they preferred based on three criteria: **(1) Naturalness, (2) Expressiveness, and (3) Lip-sync quality.** The order of the videos was randomized to avoid bias.

The results, shown in Figure 5, indicate a strong and consistent user preference for our model across all categories. Notably, the preference for "Expressiveness" was the most pronounced, with our model being chosen over 70% of the time. This qualitative feedback strongly supports our quantitative findings and confirms that our focus on punchline understanding translates into a more engaging and perceptually superior viewing experience.

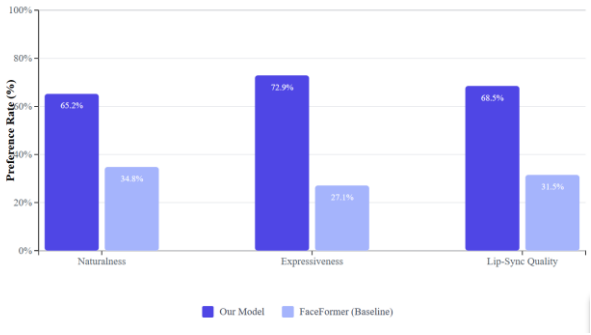


Figure 5: User study results. Participants showed a significant preference for our model over the FaceFormer baseline across all evaluation criteria.

4.4 Generalization to unseen data

To test our model's robustness and ability to generalize to out-of-domain audio, we used it to generate animations from clips taken from the LibriSpeech dataset. This audio corpus features speakers, accents, and recording conditions that were not part of the VOCASET training data. As shown in Figure 6, the model successfully generates coherent and well-synchronized animations without any signs of degradation. This result demonstrates that the model has learned a generalizable mapping from speech to facial motion and is not overfitting to the specific acoustic or speaker characteristics of the training set, confirming its strong generalization capabilities.

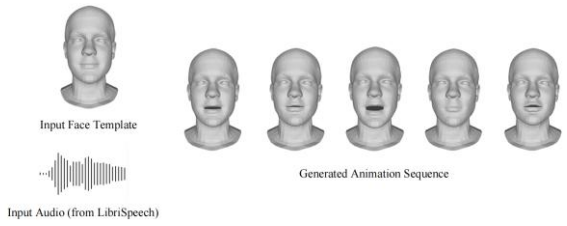


Figure 6: Animation results on an unseen audio clip from the LibriSpeech dataset, demonstrating the model's strong generalization capabilities.

5 Discussion

Our framework's superior performance in both geometric accuracy and perceived expressiveness, validated quantitatively and through user studies, is a direct result of its synergistic architectural design. The foundation is the Multimodal Punchline-Aware Feature Extractor, which leverages a large language model to grasp contextual and semantic nuances that purely audio-based systems miss, as confirmed by our ablation study. This high-level understanding of communicative intent guides our core innovation: the Punchline-Driven Hierarchical Animator (PDHA). Unlike monolithic models like FaceFormer that apply a single mapping to the entire face, the PDHA's functional decomposition allows for specialized control, enabling it to channel expressive energy into the upper face during a punchline while preserving the articulatory precision of the mouth region. A final Cross-Modal Temporal Fusion Decoder then provides a crucial micro-level refinement, ensuring precise temporal alignment between motion and audio. This event-driven approach, which focuses on rendering specific expressive climaxes, fundamentally distinguishes our work from traditional global emotion-conditioned models that apply a static affective style. Furthermore, while other recent LLM-driven systems have targeted full-body gestures, our work is uniquely focused on the nuanced domain of 3D facial animation, making it, to our knowledge, the first to explicitly model a communicative device like the punchline to drive expressive synthesis.

Furthermore, while the current model is specialized for detecting and animating punchlines, the underlying framework is highly extensible to other forms of expressive speech, such as sarcasm or surprise. These phenomena are also characterized by unique multimodal cues—a mismatch between positive words and negative prosody for sarcasm, or a sharp acoustic startle for surprise. We posit that our punchline detection module could be retrained and transformed into a more general-purpose "expressive moment detector." By curating a dataset with labels for these diverse speech acts, the model could learn to recognize a wider array of semantic and prosodic patterns. This would allow the hierarchical animator to generate context-appropriate facial expressions for a much broader range of communicative intents, moving closer to a truly general-purpose expressive animation system. While our test on the LibriSpeech dataset demonstrates strong generalization to unseen speakers, we acknowledge that the model's robustness under more challenging conditions remains an open question. Future work should rigorously evaluate the framework's performance on audio with varying levels of background noise, as well as its applicability across different languages and cultural contexts, which may feature distinct prosodic and expressive patterns.

6 Conclusion

In this paper, we introduced a novel 3D facial animation synthesis framework for speech, leveraging the potential of Multimodal Large Language Models to acquire a profound semantic representation of the input. Our key contribution is building a system that goes beyond phonetic accuracy to capture and animate the expressivity peak of speech, such as punchlines. We addressed the shortcomings of existing methods by proposing a multi-stage architecture consisting of a Multimodal Punchline-Aware Feature Extractor, a Punchline-Driven Hierarchical Animator (PDHA), and a Cross-Modal Temporal Fusion Decoder. The architecture allows our model to first identify points of maximum semantic relevance and then transform them into detailed, anatomically realistic facial movements in an orchestrated, region-by-region manner.

The extensive experiments on the VOCASET benchmark and LibriSpeech corpus firmly establish the effectiveness of our approach. Not only did our method achieve a new state-of-the-art in both geometric accuracy and lip-sync precision, but also significantly outperformed others in terms of ability to generate expressive animations, as measured by our proposed Punchline Expressiveness Score. Empirical support by our comprehensive ablation studies verified the central role of each component in our architecture, unveiling the synergistic benefits of combined multimodal feature extraction, hierarchical animation, and temporal fusion.

To the future, this work presents some very promising directions for future research. The concept of punchline-sensitive, hierarchical animator is in no way restricted to facial animation and could be extended to producing full-body gesture and motion as well, in order to construct more complete and expressive virtual characters. Further advanced emotional classifiers and context-sensitive models may also be incorporated in future work to monitor an even wider range of expressive nuances beyond punchlines. Finally, making the system real-time efficient can unlock an entire new realm of interactive applications in virtual reality, game playing, and human-computer interaction. To conclude, our research represents a significant step towards creating virtual characters that can interact with the same richness and expressiveness as individuals.

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Visual Preference Modeling and Optimization in Graphic Design via Feature Encoding and Apriori Rule Mining

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Graphic design currently lacks computationally accurate methods for identifying and optimizing user visual preferences, hindering personalized and precise design outcomes. This paper presents a computational method integrating multidimensional feature encoding and Apriori rule mining to extract interpretable visual preference patterns from user feedback, enabling targeted design optimization. A multidimensional feature matrix encompassing color, layout, font, and graphic structure is constructed and encoded into a standardized preference dataset derived from 1280 user-selected design samples. The Apriori algorithm extracts high-confidence association rules linking visual element attributes to user preference outcomes, filtering representative combinations with minimum support 0.05 and confidence 0.6. Rule sets are vectorized to represent structured user group preferences, and a preference pattern map is generated via K-means clustering with five clusters, achieving an average silhouette coefficient of 0.63. High-confidence rules are embedded as constraints in an automated design generation module, reconstructing visual solutions aligned with user preferences, validated at 89.2% extraction accuracy under support threshold 0.09. Experimental validation confirms 89.2% preference extraction accuracy at support threshold 0.09 and silhouette coefficient 0.63 for five clusters, demonstrating effectiveness and adaptability in preference modeling and optimization.

Povzetek: Razvita je metoda za modeliranje vizualnih preferenc v grafičnem oblikovanju z večdimenzionalnim kodiranjem značilk in rudarjenjem asociacijskih pravil Apriori. Pravila se uporabijo za gručenje uporabnikov in optimizacijo oblikovalskih rešitev, kar omogoča razložljivo in podatkovno podprto prilagajanje oblikovanja.

1 Introduction

Existing research on rule extraction suffers from insufficient modeling capabilities and a lack of structured expression, making it difficult to systematically extract stable and interpretable visual preference rules from user feedback. This study aims to verify the effectiveness of association rule mining methods in modeling visual preferences in graphic design and proposes three core hypotheses. First, a multidimensional feature encoding system constructed based on user behavior feedback can effectively improve the Apriori algorithm's ability to extract high-confidence visual preference rules. Second, vectorizing and clustering high-confidence rules can generate a semantically interpretable map of user preference patterns. Third, embedding such rules into an automated design generation module can more stably output visual solutions that meet user preferences across cross-task scenarios compared to traditional feature dimensionality reduction or ensemble learning methods. The proposed method constructs a multidimensional visual feature matrix and combines it with user behavioral feedback to generate standardized preference labels. Then, the Apriori algorithm is used to mine high-confidence association rules, which are then vectorized and clustered to form a user preference pattern map. Finally, these rules are embedded in an automatic design element combination module for targeted reconstruction. This entire process, from data representation and rule mining to structure identification and result reconstruction, systematically addresses the shortcomings of existing research in modeling capabilities and structural representation, ensuring that the extracted preference rules are stable and interpretable, directly serving the design optimization goal. Faced with diverse user aesthetic preferences and complex media environments, traditional graphic design methods often rely on designers' subjective experience and lack systematic integration and quantitative analysis of user visual preference data [1], [2]. This approach struggles to provide targeted visual expression when faced with large-scale design demands or diverse user groups, resulting in a disconnect between design output and user perception [3], [4]. Existing research on summarizing design experience in graphic design visual elements has a

relatively mature cognitive system, but mapping user preference behavior data into computable visual patterns is still in the exploratory stage [5], [6]. At the same time, the increasingly diverse forms of user feedback on graphic design, such as ratings, click behavior, and browsing time, make extracting structural and pattern-based preference information from them a key challenge in current research [7], [8]. The lack of an effective feature encoding system limits the construction of a structural mapping relationship between user preferences and design elements, while the sparsity and interpretability of association rules further exacerbate the uncertainty in the process of visual preference pattern recognition [9], [10]. Therefore, establishing a computable feature model of design samples and systematically extracting stable preference patterns from user feedback to provide a basis for optimizing and recommending design elements has become a core issue in the current intelligent transformation of graphic design [11], [12]. The core contribution of this research lies in the construction of a complete technical chain from visual feature encoding to preference rule mining and design optimization. By structurally linking user behavioral feedback with multidimensional visual element attributes, a computational modeling of user visual preferences is achieved. This proposed method breaks through the limitations of traditional design, which relies on subjective experience and provides a data-driven personalized optimization framework for the graphic design field. This framework not only improves the accuracy of preference identification but also ensures the semantic interpretability of the extracted rules, thus supporting subsequent design generation and recommendation tasks. To address these issues, this paper introduces a rule-mining-driven visual element recognition and optimization method, focusing on the inadequate modeling and lack of structured expression in existing research on visual preference rule extraction. First, a visual element feature matrix encompassing multiple dimensions, including color type, layout form, font style, and graphic structure, is constructed and combined with user feedback to construct a standardized design preference dataset, ensuring data comparability in terms of dimensional consistency and category distinction. Furthermore, the Apriori association rule algorithm is used to mine patterns in the relationship between visual element attributes and user preference results, identifying effective rule sets with high support and confidence. The preference information is then transformed into structured input variables through rule vectorization. Subsequently, the KM clustering algorithm is used to group the rule vectors and generate preference pattern maps for different user groups, capturing the distribution patterns of group preference characteristics. Finally, the high-confidence rule set is embedded as a design logic constraint in the element automatic combination module, enabling personalized reconstruction and optimization of design results. This method integrates the entire process from design data characterization, preference information mining, and pattern structure recognition to visual result reconstruction, providing data support and a logical framework for the construction of intelligent design assistance systems. It has practical value and research significance in improving visual expression accuracy, user matching, and design solution optimization capabilities.

2 Related works

Existing research focuses on the mapping mechanism between visual elements and user behavior. However, in the context of graphic design, structuring the modeling of visual element attributes and user preferences remains a research difficulty. Pan et al. [13] proposed a personalized emotion recognition framework based on convolutional neural networks. By analyzing user facial expressions and visual elements of design works, they can accurately identify and classify emotional expressions in graphic design, thereby assisting designers to more effectively convey and stimulate the audience's emotional resonance. This focus on the user's emotional state provides technical support for understanding how design works to trigger visual feedback. Kong et al. [14] combined design principles with a data-driven ranking model to build an automated suggestion system for graphic design aesthetic optimization. They used learned human aesthetic preferences to evaluate and optimize the generated candidate solutions, thereby improving the efficiency and quality of the design process. This method emphasized the feasibility of iterative improvement based on existing designs. Gbadegbe et al. [15], based on the expectancy value theory and Bronfenbrenner ecosystem theory, used a quantitative research method to analyze the factors affecting the graphic design preferences of 340 visual arts students in Ghana, revealing how personal motivation, design ecosystem, and multiple attributes jointly drive students to choose graphic design. This study, drawing from an educational context, expands understanding of the mechanisms underlying design preference formation. However, none of these studies delve into the complexity and uncertainty inherent in modeling visual preferences due to individual differences.

These studies have made some progress in emotion recognition and aesthetic optimization, but they often focus on modeling user perception and lack a systematic exploration of the structural connections between design elements and preferences. Particularly in the context of graphic design, a computational modeling framework for mapping the combination of visual elements to user preferences has yet to emerge, making it difficult to effectively implement design optimization tasks.

In the area of rule mining methods and their application in design optimization, existing research has explored multiple levels of algorithm improvement and cross-domain transfer. Liao S et al. [16]conducted clustering and association rule mining on survey data from 2011 Taiwanese TikTok users to generate user profiles and identify social interaction patterns, providing evidence that TikTok transcends traditional social media development paradigms. Li Y et al. [17] proposed the MCoR-Miner algorithm for maximal co-occurrence nonoverlapping sequential rule mining using depth-first search and indexing mechanisms, demonstrating superior efficiency and recommendation performance compared to

existing methods. In addition, Akgul et al. [18] combined fuzzy language summarization with genetic algorithms to extract fuzzy rules between emotional needs and product design form elements, and verified its effectiveness by comparing it with the results of fuzzy association rule mining, providing an operational technical path for the systematic transformation of emotional needs in complex product design. This method extends rule mining from structured data to the mapping relationship at the semantic level. However, these studies have largely focused on improving algorithmic performance or discovering rules in specific domains, but have not adequately addressed the complex aesthetic relationships between visual elements and the dynamic evolution of user preferences in the context of graphic design. Currently, there is a lack of rule mining methods specifically tailored to graphic design tasks to extract structured visual preference rules from user behavioral feedback, nor is there a rule-driven modeling system for design optimization.

3 Visual preference recognition and rule modeling methods

3.1 Construction of feature coding for graphic visual elements

Visual preference modeling is based on the structured expression of design features. The study constructs a multi-dimensional joint feature vector system to quantify the visual attributes of graphic design samples in terms of color, layout, font, and graphic structure. The color dimension is represented by the HSV (Hue, Saturation, Value) color space, and the ratio vector is constructed based on the pixel density of the main color distribution [19], [20], $C=[c_1,c_2,...,c_k]$, where c_k is the proportion of the (x_c,y_c) color kth categories [21], [22], and the sum is 1.

$$L_b=\sqrt{(x_c-x_0)^2+(y_c-y_0)^2} \tag{1}$$

(x_0,y_0) is the coordinate of the center point of the image. The graphic structure dimension constructs a compactness index through the contour geometry ratio:

$$G_c=\frac{A_g}{A_b} \tag{2}$$

A_g is the actual area of the graphic, and A_b is the area of the minimum enclosing rectangle. Font style extraction uses a pretrained convolutional neural network to extract embedding vectors. Principal component analysis (PCA) is then used to reduce the dimensionality of the font to generate a fixed-length high-dimensional representation, $F=[f_1,f_2,...,f_m]$, where m represents the number of dimensions after dimensionality reduction. The final unified visual feature vector has one hundred ninety two dimensions, composed of three color ratio components, one layout offset value, one graphic compactness value, and one hundred eighty seven dimensions from the PCA-reduced font embedding.

The above-mentioned encodings are concatenated to form a unified visual feature vector, $V=[C,L_b,\mathrm{F},G_c]$, which is used to represent the visual feature structure of a single design sample. Table 1 shows the schematic structure of the sample encoding, demonstrating the numerical representation of each attribute in a unified format:

Table 1: Multidimensional visual feature encoding of design samples

Sample ID	Color vector C main color ratio	Layout offset L_b	Graphics compactness G_c
S01	[0.41, 0.35, 0.24]	0.126	0.782
S02	[0.22, 0.55, 0.23]	0.294	0.605
S03	[0.48, 0.31, 0.21]	0.102	0.863
S04	[0.36, 0.28, 0.36]	0.189	0.712
S05	[0.33, 0.46, 0.21]	0.275	0.643

In Table 1, the color ratio vector, layout offset, and graphic compactness are presented in specific numerical form. The font style features are extracted through a pre-trained convolutional neural network and reduced in dimension by PCA to form a high-dimensional embedding vector, which is not listed in Table 1 due to its high dimension. This visual feature vector fully covers the four-dimensional attributes of color, layout, font, and graphic structure, with a total dimension of 192. Among them, the font dimension contributes 187 dimensions after principal component analysis compression, forming a standardized data structure for subsequent association rule mining.

All samples form a feature matrix $X\in\mathrm{R}^{n\times d}$, where n represents the number of samples, and d represents the number of feature dimensions for each sample. This matrix serves as the basic data interface for subsequent preference modeling and rule mining, ensuring numerical alignment and structural adaptation between the encoding and model layers.

3.2 User behavior data and visual preference label generation

The generation of user visual preference labels uses behavioral feedback data as input, constructing a structured preference mapping system to support subsequent rule learning tasks. The original behavior data matrix is denoted as $R=r_{ij}^{(k)}$, where $r_{ij}^{(k)}$ represents the response value of user i to the design sample j on the behavior dimension of category k. To unify the numerical scale of each type of feedback, the range normalization method is used to independently standardize each type of feedback [23], [24]. The normalization result is defined as:

$$\hat{r}_{ij}=\frac{r_{ij}-min(r_i)}{max(r_i)-min(r_i)} \tag{3}$$

$max(r_i)$ and $min(r_i)$ represent the maximum and minimum values of all feedback from the user i, and $\hat{r}_{ij} \in [0,1]$.

Each element in the original behavioral data matrix represents a specific user's response to a specific behavioral dimension of a designed sample. To ensure numerical comparability across different feedback types, range normalization is used to independently normalize each type of feedback. The normalized results serve as input to a weighted fusion model, which combines three types of feedback: clicks, ratings, and dwell time, to generate a single, comprehensive preference score. This process transforms multi-source, heterogeneous behavioral signals into a unified numerical representation, providing a stable and semantically clear supervisory variable for subsequent association rule mining. After the multi-source behavior signals are normalized, a weighted fusion model is used to generate a comprehensive preference score [25], [26], denoted as s_{ij}, which is calculated as follows:

$$s_{ij}=\alpha\cdot\hat{r}_{ij}^{(1)}+\beta\cdot\hat{r}_{ij}^{(2)}+\gamma\cdot\hat{r}_{ij}^{(3)},\alpha+\beta+\gamma=1 \quad (4)$$

$\hat{r}_{ij}^{(1)}$, $\hat{r}_{ij}^{(2)}$, and $\hat{r}_{ij}^{(3)}$ are the normalized results of click, rating, and duration feedback, respectively. $\alpha+\beta+\gamma=1$ and $\alpha,\beta,\gamma\in[0,1]$ are empirical weight parameters. The weight parameters α and β are set based on empirical research on the relative contribution of multi-source behavioral signals in visual preference prediction. Clicking behavior and rating behavior have a high consistency in expressing user preferences, while the explanatory power of dwell time as implicit feedback is slightly lower [27]. Through cross-validation and grid search, the parameter space is optimized, and α is finally determined to be 0.4 and β to be 0.3 to maximize the correlation between preference labels and users' actual choice behavior. This configuration remains stable on multiple independent datasets, ensuring the generalization ability of the fusion model in different scenarios. Table 2 lists the standardized behavior values and final scores of some users in different dimensions:

Table 2: Normalization of user behavior feedback and preference scores

User ID	Click normalization	Score normalized	Duration normalized	Overall preference score s_{ij}
U01	0.82	0.67	0.75	0.743
U02	0.45	0.51	0.48	0.480
U03	0.91	0.76	0.82	0.853
U04	0.63	0.69	0.65	0.660
U05	0.27	0.34	0.30	0.305

In Table 2, the raw user feedback, after normalization and weighted fusion, has clear distribution boundaries, allowing for precise mapping to preference labels. This process not only establishes a signal foundation for preference discrimination but also ensures the semantic stability and numerical rationality of the label dataset. This provides clear supervisory variables for Apriori rule mining and ensures that the rule results are consistent with behavioral responses.

Preference labels are generated based on the aforementioned scoring results, which are converted to a discrete binary form using a threshold function. Setting the global preference boundary parameter θ, the label generation function is defined as:

$$y_{ij}=\begin{cases}1, & s_{ij}\geq\theta\\ 0, & s_{ij}<\theta\end{cases} \quad (5)$$

$y_{ij}\in0,1$ indicates whether user i exhibits a positive preference for sample j. This preference label is aligned with the sample feature vectors one by one to construct a training dataset $D=(x_j,y_{ij})$, which supports subsequent high-confidence visual rule association mining. This encoding strategy ensures numerical consistency in behavioral feedback data and clear discriminant boundaries for labeling, enhancing the model's adaptability for extracting preference patterns.

3.3 Apriori-based visual element-preference association rule mining

Uncovering the potential correlation patterns between visual features and user preferences is a key step when building a design preference modeling mechanism. Let the feature vector of a design sample be $x_j\in R^d$, and its corresponding user preference label be $y_{ij}\in0,1$. The two are combined to form the labeled training sample set $D=(x_j,y_{ij})$. To map continuous-valued features to discrete item sets, a symbolic encoding operation $\phi:R^d\rightarrow I^k$ is constructed to project sample features onto a discrete attribute set I. This allows each sample to consist of a set of attribute items, forming a transaction item set T_j, satisfying the input format requirements of the Apriori algorithm.

The frequent item set F is defined as the attribute combination set, whose frequency in the preference positive example set is greater than the minimum SC σ [28], [29], expressed as:

$$F=\{I\subseteq I|\frac{|\{T_j|I\subseteq T_j\wedge y_{ij}=1\}|}{|\{T_j|y_{ij}=1\}|}\geq\sigma\} \quad (6)$$

Based on the frequent item sets, the generated association rule is in the form of $I\Rightarrow y_{ij}=1$, where I is the combination of visual elements, and the latter is the preference expression. The confidence of the rule is defined as:

$$\text{conf}\,(I \Rightarrow y_{ij}=1)=\frac{|\{T_j | I \subseteq T_j \wedge y_{ij}=1\}|}{|\{T_j | I \subseteq T_j\}|} \quad (7)$$

Rule filtering relies on a confidence threshold, retaining rule sets that satisfy conf greater than or equal to the confidence threshold [30]. Due to the exponential growth of the attribute item set space, a layered expansion and pruning strategy is employed to improve computational efficiency. Pruning is based on the Apriori principle: if the item set I is infrequent, then any superset of it is also infrequent, thus avoiding unnecessary computation.

3.4 Visual preference pattern discovery and user clustering

To achieve structured modeling of visual preference rules at the user level, a set of high-confidence rules needs to be vectorized, and a user-rule response matrix needs to be constructed as the basis for clustering. Each rule r_k corresponds to a visual element combination $a_1,a_2,...,a_s$, which is mapped to the complete set of discrete attributes I. A binary indicator vector $r_k \in 0,1^{|I|}$ is constructed, where $r_k[i]=1$ indicates whether attribute i belongs to rule r_k and is zero otherwise. After vectorizing all rules, it can obtain the rule encoding matrix $R \in 0,1^{m \times |I|}$.

Algorithm 1: Rule vectorization and constraint filtering for visual preference optimization.

Input: High-confidence association rule set R = {r₁, r₂, ..., rₙ},
Discrete attribute space A = {a₁, a₂, ..., aₘ},
Candidate design sample set D = {d₁, d₂, ..., dₖ}

Output: Filtered design candidate set D' ⊆ D,
Rule activation matrix V ∈ {0,1}^{n×k}

1: Initialize V as zero matrix of size n × k
2: for each rule $r_i \in R$ do
3: Construct binary indicator vector $v_i \in \{0,1\}^m$
4: for each attribute $a_j \in A$ do
5: if a_j is contained in r_i then
6: $v_i[j] \leftarrow 1$
7: else
8: $v_i[j] \leftarrow 0$
9: end if
10: end for
11: Store v_i as row i in V
12: end for

13: Initialize D' ← ∅
14: for each design sample $d_l \in D$ do
15: Compute response vector $s_l \in \{0,1\}^n$
16: for each rule $r_i \in R$ do
17: if d_l satisfies all attributes in r_i then
18: $s_l[i] \leftarrow 1$
19: else
20: $s_l[i] \leftarrow 0$
21: end if
22: end for
23: if sum(s_l) ≥ 1 then
24: Append d_l to D'
25: end if
26: end for

27: Return D', V

Based on this, the paper defines a rule activation vector $\mathbf{z}_i \in R^m$ for each user u_i. Its kth dimension represents the probability response value z_{ik} that the user satisfies rule r_k, calculated as follows:

$$z_{ik}=\frac{|\{j | r_k \subseteq T_j \wedge y_{ij}=1\}|}{|\{j | y_{ij}=1\}|} \quad (8)$$

T_j is the set of discrete attribute items of sample j, and $y_{ij}=1$ represents the preference expressed by user i for sample j. By traversing the rule hits of all preferred samples, the complete set of user rule vectors $Z=[\mathbf{z}_1^\top,\mathbf{z}_2^\top,...,\mathbf{z}_n^\top]^\top \in R^{n \times m}$ is obtained, which serves as the basis for expressing the preference structure space.

To identify the distribution pattern of user preference structure in the rule subspace, the KM algorithm is introduced to perform unsupervised clustering of Z. The objective function is to minimize the sum of the squared Euclidean distances from each sample to its corresponding cluster center, expressed as:

$$L_{\text{kmeans}}=\sum_{i=1}^{n} //\mathbf{z}_i-\boldsymbol{\mu}_{c(i)}//^2 \quad (9)$$

$\boldsymbol{\mu}_{c(i)}$ is the center vector of the cluster $c(i)$ to which user i belongs. By iteratively optimizing cluster centers and sample allocation, users in the same cluster maintain high consistency in their rule response structure. After cluster modeling, a user preference pattern map $P=C_1,C_2,...,C_K$ is obtained, where each cluster C_k consists of a group of users with similar distribution in the rule vector space. This structure supports subsequent design optimization, recommendation strategy embedding, and pattern consistency assessment based on preference type. Figure 1 illustrates the preference pattern modeling process based on rule vectorization and user clustering.

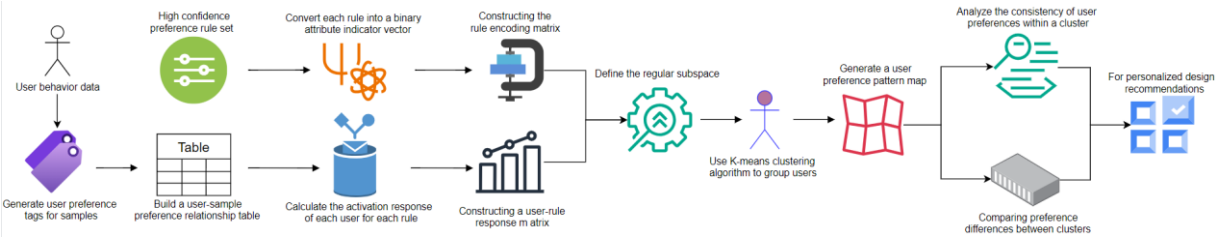


Figure 1: Preference pattern modeling based on rule vectorization and user clustering

Figure 1 shows the process of constructing a rule encoding matrix by converting high-confidence preference rules into binary attribute indicator vectors. Simultaneously, preference labels for the designed samples are generated based on actual user behavior data. Each user's activation response to each rule is further calculated to form a user-rule response matrix. Subsequently, the KM clustering algorithm is used within the rule subspace to group users and generate a visual preference pattern map. This map can be used to analyze the consistency of user preferences within a group and the differences in preferences between different groups.

3.5 Visual element combination optimization and generation

After completing preference rule mining and user pattern identification, a design generation mechanism with constraint control capabilities must be constructed to ensure that the design solution's visual attribute structure is highly consistent with high-confidence preference rules. This mechanism guides the generation of candidate design samples by converting rule sets into combined constraints and outputs the final optimization results based on feasibility screening and polynomial scoring sorting. Figure 2 shows the structural process of the design optimization mechanism driven by preference rules.

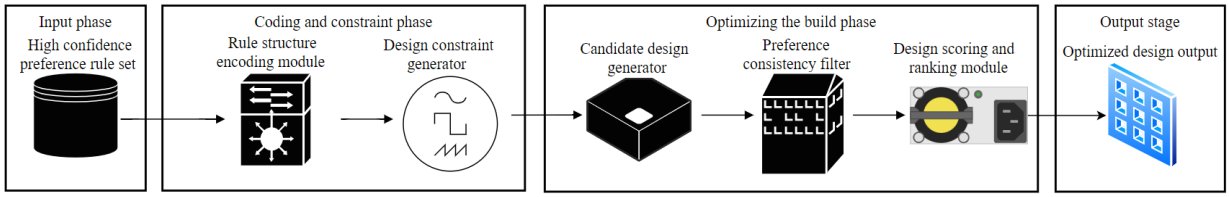


Figure 2: Preference rule constraint-driven design optimization mechanism

In Figure 2, a set of high-confidence rules is first structured and encoded to generate logical templates recognizable by the constraint system. This template then serves as the basis for constructing the conditional space for design generation. Candidate design solutions are then combined and generated based on the rule constraint logic. A preference consistency filter is then used to eliminate structurally non-compliant samples. The scoring module ranks and evaluates the filtered design set, ultimately outputting the optimal design solution that conforms to the preference rule structure. This architecture uses rules as logical input and embeds semantic knowledge into the design generation process, ensuring that the output solution is highly consistent with user preferences at the visual attribute level.

The set of high-confidence preference rules is denoted as $R=r_1,r_2,...,r_m$. Each rule r_k consists of a set of visual element attributes, which are encoded and mapped into a formal logic vector through the rule structure. The design constraint generator defines a response function $\Psi(\mathbf{s}_t,r_k)$ for each rule based on this logic template, where the value is 1 if the candidate design $\mathbf{s}_t$ satisfies the visual configuration in rule r_k, and 0 otherwise:

$$\Psi(\mathbf{s}_t,r_k)=\begin{cases}1, & \text{If design } s_t \text{ Satisfy the rules } r_k\\ 0, & \text{otherwise}\end{cases} \tag{10}$$

Based on this response function, a multi-rule weighted scoring model is defined to evaluate the preference fit of candidate design solutions:

$$J(\mathbf{s}_t)=\sum_{k=1}^{m}\boldsymbol{\alpha}_k\cdot\Psi(\mathbf{s}_t,r_k) \tag{11}$$

The confidence weight of the $\boldsymbol{\alpha}_k$ in rule r_k represents the structural importance of the rule in the preference distribution. A candidate design sample set is dynamically constructed from the visual element attribute space using a stratified sampling strategy. The number of samples is adaptively adjusted based on the coverage of the constraint rules, ensuring efficient exploration of the solution space while satisfying high-confidence preference rules. This strategy avoids enumerative exhaustive search to improve computational efficiency. Unlike black-box methods such as generative adversarial networks, it maintains an explicit connection between the generation process and the rule logic. The generated candidate set undergoes consistency filtering and then enters the scoring and ranking phase, ultimately outputting the optimal solution. The sample generator constructs the candidate set $\mathbf{s}_1,\mathbf{s}_2,...,\mathbf{s}_T$ from the design space S, and then uses the consistency filter to eliminate samples that do not meet the preference response threshold τ:

$$\mathbf{S}_{\text{valid}}=\left\{\mathbf{s}_t\in S\,\middle|\,\sum_{k=1}^{m}\Psi(\mathbf{s}_t,r_k)\geq\tau\right\} \tag{12}$$

Finally, the design with the largest score is selected from the samples that meet the response constraints as the final optimization output:

$$\mathbf{s}^*=\arg\max_{\mathbf{s}_t\in\mathbf{S}_{\text{valid}}}J(\mathbf{s}_t) \tag{13}$$

This mechanism achieves a combined optimization of rule-driven structural control and scoring-driven optimization, ensuring both logical consistency and preference matching when outputting visual design results. This creates a complete closed-loop from rule mining to automated optimization generation.

4 Experimental setup and implementation process

4.1 Planar visual element dataset construction and experimental configuration

The dataset contains 1,280 graphic design samples from commercial visual communication and digital media content, covering advertisements, brand logos, publication covers, and social platform interfaces. The visual element attributes, such as main color distribution, layout

structure, font style, and graphic composition, are all structurally annotated. User feedback is collected via offline platforms and web interactions, with all data anonymized to ensure participant privacy during processing. In the experimental data construction stage, the study collects a graphic design dataset for visual preference modeling based on commercial visual communication (covering commercial advertising, brand identity design, publication covers, etc.) and digital media content (covering social platforms, data visualization, etc.). The total number of image samples is 1,280, covering core dimensions, such as main color, typesetting, font style, and graphic composition. Each type of graphic visual element attribute constructs an attribute label system, and all samples complete the visual feature structured annotation. User feedback data comes from offline test platforms and web-based interactive behaviors. The collected indicators cover the design selection click frequency, dwell time, and explicit rating values. After normalization and conflict elimination, user preference mapping labels are generated, and a preference record matrix corresponding to the sample set is established. The platform hardware configuration is a dual-core Xeon processor with 128GB of memory and an RTX A6000 graphics card. The software development environment is Python 3.10. Data processing and algorithm training are deployed in TensorFlow 2.13 and Scikit-learn 1.4 environments, respectively.

4.2 Visual preference rule training and optimization task process

During the model training and task execution phases, this study uses a unified preference modeling and rule-driven optimization process, completing a closed-loop design from visual sample input to optimization output. The model training phase uses the pre-processed 192-dimensional sample input matrix as a foundation, loading visual feature vectors and user preference labels, and constructing a mapping space between visual attributes and behavioral labels. Based on this, the Apriori rule mining algorithm constructs frequent item sets and confidence matrices. Minimum support and minimum confidence serve as constraint thresholds to dynamically adjust the rule selection process, ultimately forming a complete set of rules. The rule set is then vectorized and clustered, mapped to the corresponding user group index, and the modeling of the multi-preference subset distribution structure is realized. To ensure that the generated solution strictly matches the user preference rules, the system builds a design optimization engine based on preference constraints. Its core strategy is to introduce a logical condition verification mechanism when generating design candidates. All candidate outputs must meet the structural conditions of at least one set of high-confidence preference rule items. To clarify the process of task and parameter configuration at each stage, Table 3 shows the key task parameter composition during the training phase and optimization engine initialization process.

Table 3: Preference rule model training and design optimization task configuration parameters

Stage	Input data dimensions	Total sample size	Core operating procedures	Parameter settings
Data loading	192	1280	Read visual feature vectors and preference labels	Batch size: 128, Loading method: Memory mapping
Rule mining	192	1280	Constructing frequent itemsets and confidence matrices	Minimum support: 0.05, minimum confidence: 0.6
Rule filtering	-	894	Filter weakly correlated rules to generate high-confidence rule sets	Redundancy threshold: 0.15, maximum itemset length: 5
Rule vectorization encoding	-	1280	Converting rule sets into structured vector representations	Encoding method: sparse matrix mapping, dimension compression: no
Preference-constrained optimization engine	192	Dynamic	Embedded logic matching mechanism for solution generation and filtering	Matching strategy: minimum coverage, number of execution threads: 4

As shown in Table 3, frequent item set generation and high-confidence rule screening constitute the bulk of the rule mining phase, determining the size of the constraint space for the subsequent optimization engine. The rule vectorization step implements the structural expression of preference logic, providing precision support for clustering and optimization. The optimization engine configuration parameters in the final phase directly impact design generation efficiency and preference coverage. This structure ensures logical continuity and parameter control throughout the entire task chain, ensuring consistent functional coupling between objectives at each stage.

During the rule mining phase, the maximum item set length is set to 5, and the redundancy threshold is set to 0.15, aiming to balance the expressiveness of the rule structure with generalization performance. Excessively long item sets can lead to sparse rule coverage, reducing

cross-scenario adaptability; excessive redundancy weakens the discriminability between rules and affects the accuracy of identifying user preference patterns. This parameter combination, through multiple rounds of cross-validation, maintains a high-confidence rule set size while ensuring that the generated rules have clear semantic boundaries, avoiding overfitting to specific behavioral data and losing the universal explanatory power of visual element combination patterns.

This process maintains the consistency of preference logic in the training and generation stages, ensures the user fit and rule interpretation ability of the output results, and provides a basic comparison structure for subsequent generalization verification.

5 Experimental results analysis and preference recognition evaluation

5.1 Evaluation indicators for visual preference rule extraction

In the performance analysis stage of visual preference rule extraction, to comprehensively evaluate the performance differences of this method in actual design tasks, the recognition effects of five different rule mining and feature modeling strategies under multiple SCs are compared. The processing logic of various methods in preference modeling is essentially different. Among them, PCA and Information Gain (IG) methods focus on screening preference dimensions from the perspective of dimension compression and feature importance; Random Forest (RF) method uses an integrated tree structure to build an attribute selection scoring mechanism; FP-Growth (Frequent Pattern Growth) directly mines potential common structures from the candidate set scale expansion items. The method in this paper combines visual encoding and Apriori logic rule screening, and uses user behavior-driven preference labels as supervisory variables to construct a multidimensional item set mapping mechanism, thereby improving rule coverage and semantic accuracy. The evaluation indicators use precision and recall to characterize the performance of preference determination, while the number of rules and average confidence are used as indicators of structural integrity and credibility. Figure 3 shows the comparison of the preference rule extraction performance of each method under different SCs. Notes: N represents the number of rules; C represents the average confidence; P represents precision; R represents recall.

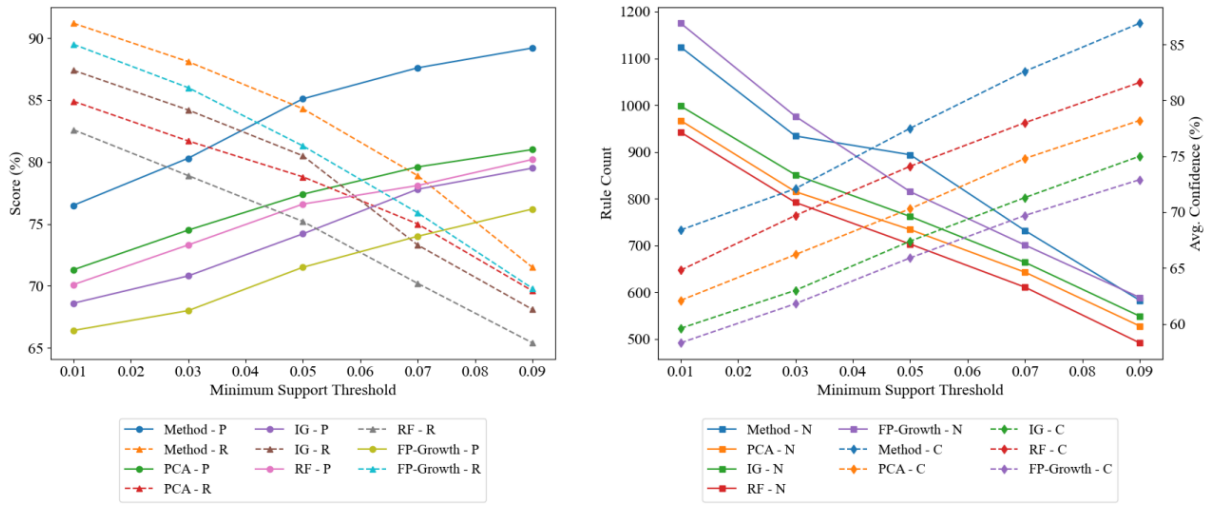


Figure 3: Comparison of preference rule extraction performance of various methods at different SCs

In Figure 3, as the SC increases from 0.01 to 0.09, the precision of the proposed method steadily increases from 76.5% to 89.2%, demonstrating a consistent trend of high-confidence rule sets enhancing preference accuracy. In contrast, the PCA method achieves a final precision of only 81.0%, and its recall decreases from 84.9% to 69.6%, indicating that the dimensionality compression process interferes with the identification of preference boundaries. The FP-Growth method shows a high recall rate in the low support range, reaching 89.5% at 0.01. However, as the SC increases, the confidence increases slowly, and the number of rules drops sharply to 589, reflecting its lack of a structural compression mechanism for rule generalization ability.

The proposed method extracts 894 high-confidence rules at 0.05 support, with an average confidence of 77.5%, which is much higher than 70.3% and 67.4% of PCA and IG, respectively. This is mainly attributed to the fact that the proposed method introduces a behavior-driven supervision strategy in the rule generation stage, enabling the rules to have stronger user-perceived matching capabilities. Based on the above indicators, the proposed method consistently maintains a leading trend within the support range, validating its optimization advantages in designing visual preference modeling.

Based on the above indicators, the proposed method continues to maintain a leading trend within the support range. Its optimization advantage comes from the fact that the behavior-driven supervision strategy strengthens the semantic mapping between visual element combinations and user preferences in the rule generation stage, avoiding the loss of key perceptual information in the unsupervised dimensionality reduction process. At the same time, the discretized attribute space and the frequent itemset

pruning mechanism synergistically improve the structural generalization ability of high-confidence rules.

5.2 Evaluation of visual preference group clustering

After extracting high-confidence preference rules, the study further models and analyzes the group structure of users in the rule response space. The selection of K-Means for clustering is grounded in its computational efficiency and interpretability within the context of this study's structured rule vector space. The cluster number k is determined by maximizing the average silhouette coefficient across a range of candidate values from three to seven. This metric evaluates intra-cluster cohesion and inter-cluster separation, providing an objective criterion for identifying the optimal partitioning that best reflects the underlying structure of user preference patterns within the rule response space. The rule vectors derived from Apriori mining are inherently discrete and sparse, forming a feature space where centroid-based partitioning aligns with the objective of identifying distinct, interpretable preference groups. Alternative density-based or hierarchical methods often require parameter tuning sensitive to data distribution or produce less intuitive cluster boundaries, which may obscure the direct mapping between rule sets and user segments essential for subsequent design optimization. K-Means provides a stable, deterministic outcome suitable for integrating into the constraint-driven generation pipeline, ensuring consistent cluster assignments across iterations necessary for evaluating recommendation performance. To verify the impact of different modeling approaches on user clustering, user response matrices are constructed based on the five feature extraction strategies described above, and the KM clustering algorithm is uniformly used for multi-clustering. The average silhouette coefficient and the Davies-Bouldin Index (DBI) are used as the primary indicators in the evaluation process. The former reflects intra-cluster consistency, while the latter measures inter-cluster separability, comprehensively characterizing the rationality of the cluster structure and the clarity of its boundaries. Figure 4 shows the trends of these two indicators for different cluster numbers.

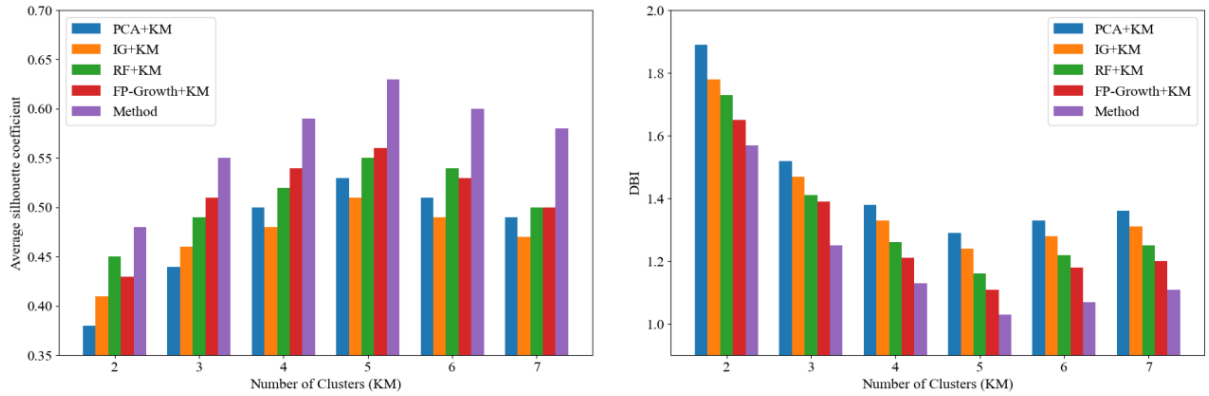


Figure 4: Performance evaluation of user preference clustering structures using different methods

In Figure 4, when the KM is 5, the silhouette coefficient of the proposed method reaches 0.63, 0.1 higher than the PCA solution. This gain is primarily due to the expressive power of the rule vector in the attribute combination dimension, enhancing the discriminability of user preference features. At the same KM value, the DBI drops to 1.03, significantly lower than IG's 1.24 and FP-Growth's 1.11. This is because the behavior-driven rule vector effectively eliminates redundant noise in some preference expressions, thereby compressing the fuzzy intervals of cluster boundaries. Except for the optimal point at KM of 5, the proposed method maintains high silhouette values and low separation index throughout the entire KM range from 3 to 7, demonstrating its robust ability to identify user preference structures. A larger silhouette coefficient value indicates a higher probability that a sample point is correctly assigned to the current cluster and a higher degree of differentiation from other clusters. Therefore, a higher silhouette coefficient indicates better clustering results. This demonstrates that the preference rule model constructed by this method effectively improves the stability and semantic consistency of cluster boundaries. Results show that the preference rule model, which co-encodes behavioral feedback and visual features, constructs a clear and separable user pattern structure within multi-cluster partitioning, effectively improving the stability and semantic consistency of cluster boundaries.

5.3 User satisfaction verification of the optimized design scheme

To further verify whether the perceived differences in recommended design solutions across different preference patterns exhibit structural consistency, this study categorizes user groups into five preference groups and constructs an evaluation system for group response consistency and recommendation acceptance rate. In the consistency analysis, the mean cosine similarity of ratings is used to measure the convergence of responses to the same recommended solution across users within a cluster, focusing on the model's ability to maintain group behavioral stability. The acceptance rate evaluation uses the proportion of users with scores higher than the preference threshold as an indicator to measure the effective adaptation of the recommendation scheme in the target preference group. The left sub-figure of Figure 5 shows the distribution differences of the consistency

scores of the above five methods in each cluster, and the right sub-figure shows the corresponding recommendation acceptance rate performance.

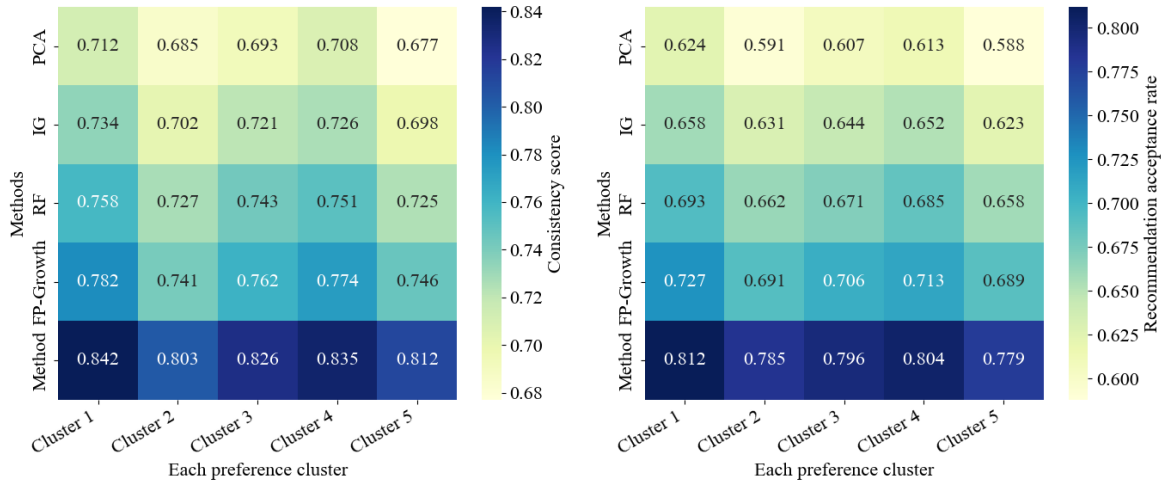


Figure 5: Comparison of design response consistency and acceptance rates of different methods in each preference group

In Figure 5, in terms of consistency scores, the proposed method achieves mean scores of 0.842 and 0.826 in Clusters 1 and 3, respectively. These scores are significantly higher than FP-Growth's scores of 0.782 and 0.762, and are 0.13 and 0.133 higher than the PCA method. This demonstrates that the preference modeling strategy based on the combination of visual element encoding and the Apriori rule is more effective in enhancing the expressive power of rating structures within a group. This advantage is not limited to a single cluster but is consistently demonstrated across all preference groups. In Clusters 2 and 4, the consistency score of this method is also higher than that of the other four methods, which are 0.803 and 0.835, respectively.

In the evaluation of recommendation acceptance rate, this method reaches 0.812 in Cluster 1, which is 0.085 and 0.119 higher than FP-Growth and RF, respectively, indicating that the recommended design scheme has a larger proportion of high-scoring feedback in this preference group, and the model output is closer to its explicit preference trend. In Cluster 5, FP-Growth and RF are close in value, but this method still leads with 0.779, indicating that it still has a robustness advantage in the boundary preference cluster. These results demonstrate that combining visual features with behavioral responses for rule-driven modeling significantly improves the consistency of rating structures and the strength of output acceptance within user clusters, validating this strategy's broad adaptability and structural stability for identifying preference patterns.

5.4 Comparative analysis of the distribution of visual elements in graphic designs after design optimization

To evaluate the actual impact of the optimization mechanism in improving the matching degree between visual structure and user preferences, this section conducts analysis based on the two dimensions of color distribution and layout structure, and compares the structural performance of the results generated by each method from the two aspects of the proportional difference of the visual main tone and the spatial offset of the typesetting center of gravity. At the color level, the average primary color ratio is used to measure the color balance of design samples under five main tones. The purpose is to examine whether the recommendation mechanism has color bias or concentration tendencies. The layout dimension uses the image center of gravity offset as a quantitative indicator of the balance of the layout structure, reflecting whether the optimization leads to the generation of a more visually stable layout composition. The dispersion of these offset values across all color categories is quantified by their interquartile range to assess structural consistency. The five color types represent different visual expression preferences. Cool blues are often used for rational and technological styles, while warm reds tend to be emotionally stimulating and visually impactful. Grayscale structures convey a simple and neutral visual tone; vibrant yellow has attention-directing properties; deep green is often associated with natural compositions. The left sub-figure in Figure 6 shows the average primary color proportions for each method under the five color categories, while the right sub-figure shows the distribution of layout offset values for the corresponding color samples.

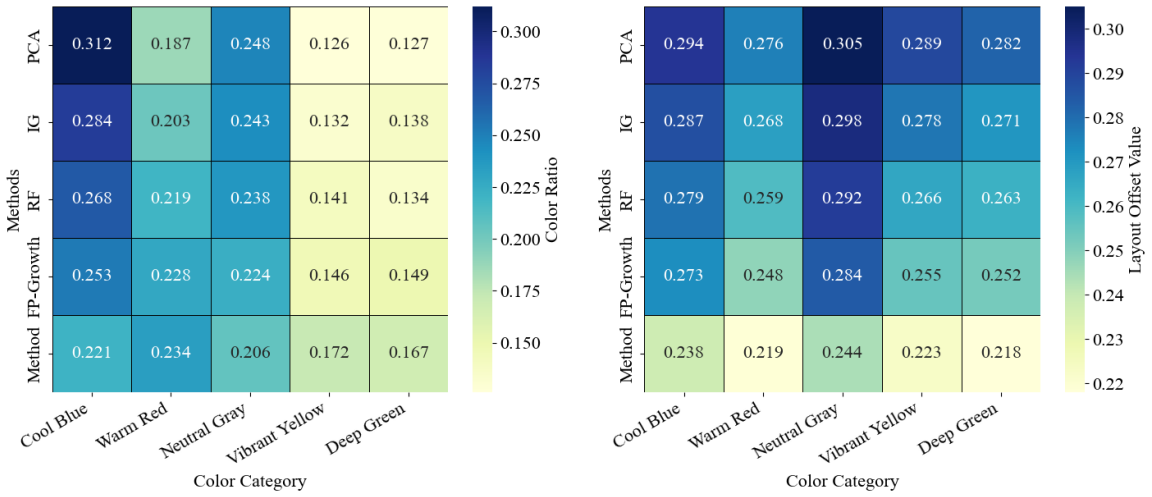


Figure 6: Multi-method comparison of visual dominant tone distribution and typographic structure shift in design optimization results

In Figure 6, both PCA and IG methods show a clear trend of cold blue dominance in the color structure distribution. The average dominant color ratio for this category in PCA is 0.312, significantly higher than that of other categories. This suggests that traditional dimensionality reduction strategies have not effectively suppressed color centralization in design solutions, and the lack of color diversity can lead to reduced preference matching accuracy. This method creates a more dispersed color structure across the five main tones. Vibrant yellow and deep green account for 0.172 and 0.167 of the totals, respectively, remaining within the low-skew range. Cool blue and warm red increase in their proportions to 0.221 and 0.234, respectively. This indicates that color selection behavior driven by high-confidence preference rules is aligned with user aesthetic intent, and the color matching strategy exhibits a clear trend toward harmony.

Regarding layout deviation, the proposed method is controlled at 0.244 or below in all color types, which is lower than the minimum deviation value of 0.248 of FP-Growth, and converges to 0.238 and 0.223 in the cold blue and vibrant yellow categories, respectively, showing the convergence enhancement effect of the layout structure in recommendation generation. The deviation values of the corresponding categories of the PCA method are 0.294 and 0.289, respectively, indicating that the problem of unstable layout structure has not been resolved. The results show that the optimization strategy based on preference rule constraints not only reduces the dominance of a single dominant tone at the color structure level but also improves the stability of the spatial composition, effectively supporting the output of preference consistency from the perspective of the input feature structure.

5.5 Testing model stability and preference generalization

In a multi-task design environment, to verify the cross-task adaptability of the preference modeling method in terms of maintaining structural rules and outputting results, it is necessary to examine its robustness and generalization capabilities under conditions of sample distribution changes. The stability evaluation uses the rule overlap rate as the core indicator to quantify the degree of intersection between the high-confidence rule sets extracted by each method in different tasks, reflecting the model's transferability at the rule structure level. The generalization ability is measured by the output consistency score, that is, the structural similarity between the recommended designs received by users with the same preferences in different tasks. This indicator focuses on evaluating the consistency of the recommendation mechanism in maintaining preferences. The five selected task scenarios encompass distinct design domains: commercial advertisements, publication covers, social platform content, data visualization interfaces, and brand identity design. Each task comprises an independent dataset of 256 samples with non-overlapping user groups, ensuring structural diversity and preventing cross-task bias. The left sub-graph in Figure 7 shows the average level of rule set overlap between different tasks for each method, and the right sub-graph depicts the consistency score of the output recommendation under the corresponding task.

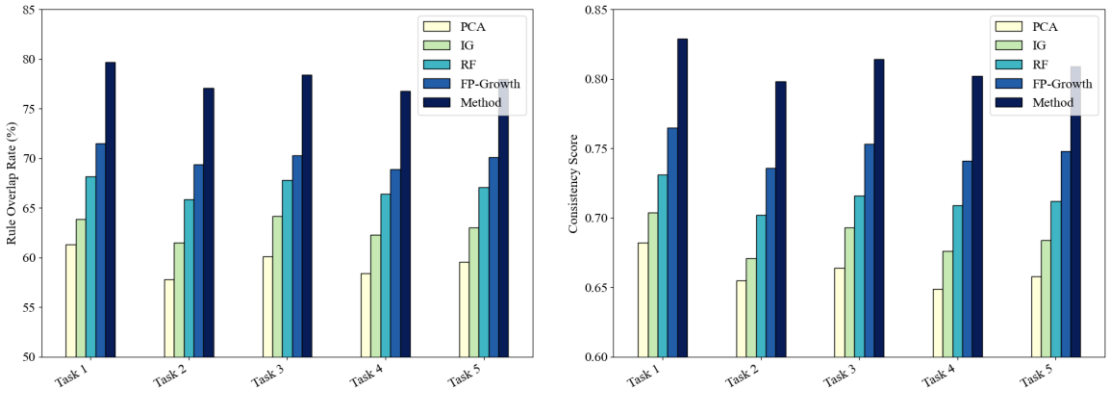


Figure 7: Comparison of different modeling methods in multi-task preference structure stability and recommendation output consistency

In Figure 7, in terms of rule structure stability, the proposed method achieves rule overlap rates of 79.7% and 78.4% in Tasks 1 and 3, respectively, which is higher than FP-Growth's 71.5% and 70.3%, a difference of over 8%, indicating that preference rules have greater structural scalability under task changes. This result stems from its user-behavior-driven multidimensional vector space construction, which improves the semantic consistency of rule generalization. In contrast, PCA achieves the lowest performance across all tasks, with an overlap rate of no more than 61.3%, indicating that its unsupervised compression-based feature set lacks structural consistency.

In terms of output consistency, the proposed method achieves scores of 0.798 on Task 2 and 0.809 on Task 5, respectively, exceeding FP-Growth by 0.062 and 0.061. This difference stems from the rule-driven generation mechanism's enhanced structural embedding of preference logic, resulting in output samples that more closely align with the user's original preference expression in terms of visual structure and dominant color distribution. The scores of IG and RF methods in Tasks 2 and 5 are concentrated between 0.671 and 0.712. The range of variation is limited by their policy frameworks that rely on local attribute contribution rates or conditional information and do not have the ability to express global preference structures. Experimental results show that the strategy of integrating user behavior responses with rule structures can effectively maintain the consistency of rule structures and the preference fit of recommendation outputs under task disturbance conditions, and has strong cross-scenario adaptability.

6 Discussion

This method demonstrates advantages over traditional modeling techniques in multidimensional evaluation. Its improved accuracy stems from a behavior-driven supervision mechanism that strengthens the semantic mapping between visual element combinations and user preferences during the rule generation phase, avoiding the loss of key perceptual information encountered in unsupervised dimensionality reduction by PCA. While FP-Growth achieves high recall at low support, its rule generalization is limited by its structural compression mechanism, resulting in a sharp decline in the size of the rule set at high support. This method constructs a user preference space by vectorizing rules, enabling K-means clustering to achieve a silhouette coefficient of 0.63, demonstrating greater internal consistency and clearer inter-cluster distinctions among the user groups it delineates. The optimized output achieves higher rating consistency and acceptance rates within each preference cluster, validating the effectiveness of embedding high-confidence rules as a constraint mechanism. In cross-task testing, both the rule overlap rate and output consistency score outperform comparable methods, demonstrating the greater adaptability of this modeling approach based on the collaborative encoding of behavioral feedback and multidimensional features. These performance advantages jointly confirm the effectiveness of this method's technical chain from feature encoding to rule mining to design optimization in solving the problems of user visual preference modeling and optimization in the field of graphic design.

7 Conclusions

This paper focuses on the accurate identification and optimization of user visual preferences in graphic design, and introduces a method that integrates feature encoding and Apriori rule mining. By constructing a multidimensional visual feature matrix including color, layout, font, and graphic structure, and combining user behavior feedback to generate standardized preference labels, the Apriori algorithm is used to extract high-confidence visual preference association rules. The rules are further vectorized and input into the KM clustering model to generate a preference pattern map of the user group. Finally, the rules are embedded as constraints in the automatic combination module of design elements to achieve personalized reconstruction of visual solutions and improve the consistency of output with user visual preferences. Experimental results show that the preference extraction accuracy of this method reaches 89.2% when the SC is 0.09, and the average silhouette coefficient reaches 0.63 when the number of clusters is 5, verifying its effectiveness and adaptability in preference modeling and design optimization. The experimental validation demonstrates superior performance compared to

alternative feature modeling and rule extraction techniques, affirming the method's advancement in achieving precise and interpretable visual preference recognition for targeted design optimization.

This study relies on behavioral data collected from specific regions to model user preferences, whose cultural background and aesthetic preferences may affect the universality of the rules. The constructed feature encoding system does not include dynamic interactions or three-dimensional visual elements, limiting the model's adaptability to complex scenarios. The current optimization mechanism is based on deterministic rule constraints and has not yet integrated generative architectures to explore a richer design space. Future work can expand the diversity of data sources, introduce multimodal perception dimensions, and explore the semantic embedding capabilities of neural network structures in layout generation to improve the system's response accuracy and output diversity to unstructured preferences.

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Fuzzy Inference-Based Safety Monitoring Framework for Substation Power Operation Sites Using IoT Sensor Networks

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An important aspect of the country's power supply is the infrastructure development of the power grid. There are a lot of people and pieces of machinery involved in power building, and it often involves teams from several industries working together. As a result, SPOS (substation power operation safety) safety management is notoriously difficult to attain. An enhanced security administration and oversight system based on the IoT with smart sensors is suggested and implemented to enhance the safety management with control of SPOS. An examination of the safety management system's building process is conducted according to the SPOS's characteristics. Intelligent sensors collect data on operational parameters, which are then sent by means of industrial gateways and Internet of Things connectivity devices. The BIM map would display the outcomes of the analysis carried out through artificial intelligence algorithms on the monitoring data. At long last, a control and management system that includes monitoring, early warning, and alarms has been built. In SPOS's safety control and administration section, the topic of smart construction site solutions is also covered. When used in conjunction with the real field system, it confirms that the safety control and management system is reasonable. Operators can make better, more proactive choices about maintenance and resource allocation because to the continual nature of the output. An example would be giving more priority to a substation with a risk index of 0.85 than one with an index of 0.65, even though both would be deemed "high risk" according to the conventional approach. Compared to previous models, this one has a greater prediction accuracy (96 percent), can appropriately produce signals of varying levels, and may serve as a reference for the development of substation safety warning, preventive, and control systems in the future.

Povzetek: Predstavljen je varnostni nadzorni okvir za elektroenergetska razdelilna mesta, ki združuje IoT senzorska omrežja in mehko logiko. Sistem omogoča sprotno ocenjevanje tveganj, zgodnje opozarjanje in večnivojsko odločanje za izboljšano varnost in zanesljivost obratovanja.

1 Introduction

Substations provide a safe haven for power circuit switching and, in certain cases, voltage conversion. In this context, "substation" means both substations along with switching stations. Due to the fact that substation equipment is often only partially deenergized for maintenance [1], [2], substations provide an inherent safety risk. An in-depth familiarity with the substation, including its aerial and subsurface line connections, is essential for the safe operation along with upkeep of the system. When cared for correctly, systems are built to be secure to use. Maintaining a safe working environment requires familiarity of the work dimension, its dangers, and its design foundation in order to do maintenance in a way that avoids risks. The (n-1) safety criteria are used for the sizing of certain electrical components in power plants along with substations, whereas the (n-2) criterion is used in nuclear power plants [3], [4]. According to the concept, safety of the grid must be ensured in the event that a component, such a transformer or circuit, is disabled or fails in an electrical grid that is expected to handle maximum transmission and distribution jobs. The installation's monitoring technology has a unique problem due to the electrical systems' ensuing redundant nature. Operators may analyze system data as per their requirements, use it to enhance the system, and establish correlations between measurement data and other power plant occurrences. This is useful for identifying the origins of temporary insulation problems, as repair crews aren't always able to respond to fault notifications in a timely manner (within a few hours), pinpoint their exact location, and remove them.

The electric traction power supply network has two modes of operation: normal and fault. Failures in the contact line, substation posts, or traction substations may lead to the fault regime [5], [6]. Several forms of electrical traction-specific protection safeguard power supply system electrical equipment against aberrant operating regimes. Commissioning protective relays in power system security applications involves using a relay test equipment to measure the operating time of the relays and the states of the breakers during various electrical failures [7], [8]. Afterwards, it would be possible to build up overcurrent protective relays to provide inverse time overcurrent security, and then compare the estimated and measured timings of the relays. Additionally, it is possible to assess the selectivity coordination of the main and backup protection systems [9], [10]. For main and backup protection, relay-relay devices should have a measured minimum CTI of more than 7.2 cycles, and fuse-relay devices should have a measured minimum CTI of more than 12.2 cycles. For various power grid applications, Table 1 details the % error with minimum CTI limitations [11], [12], [13].Table 1 illustrates the Power grid applications requiring minimal CTI restrictions and measurement percentage error.

Table 1: Power grid applications requiring minimal CTI restrictions and measurement percentage error

Type of Simulation	**Measurement Applications at Electrical Substations and Power Grids**		**Percentage Error and Minimum CTI Limits**
Power flow analysis	Power in its actual and reactive forms, frequency, voltage, current, etc.	Common monitoring	5%
		Synchro phasor	1% *
		Interconnecting DERs	1%
Electrical fault analysis (transient event states)	Differences in effectiveness between main & backup overcurrent protection systems	Primary fuse and backup relay	7.5 cycles **
		Primary and backup relays	13.6 cycles **

Here, the use of fixed equipment to pinpoint insulation faults is superior. Good layout design is essential for electrical substations in order to reduce environmental impact while providing continuous, reliable, and safe electricity. These substations are crucial parts of the power distribution network. In this post, we will go over the basics of substation layout design, including some important concepts and things to keep in mind. Industrial facility designs are based on these required clearance and distance standards. With an unwavering commitment to safety with environmental preservation as our guiding principles, precise distances are established by project specifications, local restrictions, and thorough safety evaluations. Several important factors should be considered at the Substation location to guarantee safety, reliability, and efficiency.

2 SPOS analysis

Numerous casualties in the construction business make it one of the greatest accident-prone sectors, with far-reaching consequences for workers, employers, and the community at large. A great deal of unpredictability and uncertainty permeates the outdoor setting that is typical of building development. Nowadays, there is a greater likelihood of accidents due to the simple management of building construction. The use of smart site construction in recent years has led to a considerable decrease in the accident rate at construction sites. As a result, implementing safety controls on the job site is crucial for lowering accident rates.

The following are some of the many ways in which predictive and preventative maintenance may be beneficial:

The benefits include:

- less unplanned shutdowns,
- more efficient use of personnel,
- more plant productivity,
- lower instrument management costs, and
- longer gadget life.

There is a higher risk of injury on SPOSs compared to other building sites. Many factors often need to be considered in SPOS safety control. Complex factors like as equipment, people, high-voltage transmission lines, distant locations, and early phases of inadequate power supply make management more difficult than on conventional building construction sites. This work aims to enhance safety control in power grid construction by constructing a safety control system suitable to SPOSs. Cameras for monitoring, gadgets for wireless connection, and intelligent sensors make this system possible. The control center, the environment, the equipment, and the people using them all work together in real time.

2.1 Feature of SPOS

Predictive servicing of electrical systems involves keeping devices running well by keeping tabs on their online operating status in real-time, which is achieved by regularly collecting information about the efficiency of various electrical equipment, the distribution of heat from devices, and other factors reliant on statistical data. Consequently, the computer meticulously prepares all maintenance actions using precise data. If there is a significant abnormality, it is addressed before the whole system fails. Identifying electrical equipment defects early on helps avoid major disorders from happening, which in turn decreases downtime, maintenance costs, and enhances devices' operating time. There are a lot of ways in which SPOSs vary from regular construction sites. The unique geographical location and the unique role performed are the key factors. Here are some of the SPOS's features. One may see the SPOS of a suburban region in Figure 1. Substations are often built in outlying suburban and hilly regions. The construction region has inadequate power supply and communication network coverage as a result. There could be 10kV, 35kV, 110kV, 220kV, or 500kV high-voltage transmission lines present in an SPOS. There is a higher risk of electrical mishaps on construction sites when electricity is always on.

Intelligent substation renovation and new intelligent substation construction are the two primary scenarios in which substations are built. Keeping the electricity on is an important part of intelligently transforming old substations. As a result, SPOSs encounter a more complex environment, making it harder to attain precise safety control. Equipment safety, energy and water meter monitoring, drone monitoring, electric shock prevention, staff behavior identification, and environment monitoring are all components of SPOS's safety control system. They are corresponding to the site's environmental monitoring, people monitoring, and equipment monitoring, respectively.

2.2 Equipment safety system

The construction scenes at SPOS are intricate, and there is a wide variety of construction equipment there. The current method of safety control, which relies on taking pictures of and collecting data on construction equipment using cameras, is not capable of providing complete monitoring. As a result, in order to perform thorough safety control of SPOS monitoring, this study employs a plethora of sensors. Figure 5 is a schematic depicting the SPOS gadget safety control framework. Data uploaded from all equipment monitoring systems is shown by the red dotted line in Figure 5.

There are six constituent parts that make up the overall system for controlling equipment safety. Tower cranes, elevators, unloading platforms, construction vehicles, lofty supporting molds, and deep foundation pits have all been monitored. An information transmission network, control center, and monitoring sensors make up each subsystem. Ensuring the security of the whole building site, it accomplishes the administration and control of construction scenes. In Table 2, we how each subsystem works.

Table 2: Different applications for substation monitoring

System	Function
Tower Crane Safety Monitoring System	The tower crane's activity is tracked in real-time using monitoring sensors, which also update the BIM model. The control center can supervise the tower cranes' safety in real-time.
Elevator Monitoring System	Elevator safety control using data from sensors such lift speed, load, and passenger count.
Discharge Platform Monitoring System	Indicators like tilt angle and load capacity are used for discharge platform monitoring.
Construction vehicle	Keep an eye on the whereabouts and status of construction trucks.
High support mould monitoring system	The development of the support mold's safety status monitoring was based on a great deal of monitoring indications, which allowed for the achievement of early alert of accidents.
Foundation Pit Monitoring System	Surface deformation, fissures, and other problems may be identified as they develop in real-time inside the foundation pit. The foundation pit condition monitoring is completed.

The equipment's safety control system has electric field sensors in addition to SPOS features. Near the SPOS, there are transmission lines carrying high voltage, which might cause electrocution in the event of a construction

disaster. Thus, in order to implement the control system for preventing electric shock during equipment assembly, electric field sensors are used. To pinpoint the exact spot of an accident, position sensors are essential for construction equipment, which is constantly moving. An electric shock protection warning based on two dimensions—electric field size as well as geographical location—can be realized with the integration of positioning equipment into the electric field sensor. This study updates the electric field sensor design to include an acceleration sensor, allowing for more accurate localization of the moving object. This method guarantees precise positioning by achieving real-time adjustment of the electric field sensor's location. Because environmental factors like humidity and temperature may influence electric field measurements. As a result, the electric field sensor incorporates temperature and humidity measurements into its architecture. The exactitude of the electric field analysis may be assured by combining real-time temperature and humidity readings with the electric field sensor's observed values.

2.3 Equipment status characteristics

Surge arresters, capacitor banks, voltage transformers, current transformers, circuit breakers, and transformers make up the bulk of a substation's high-voltage electrical equipment. The reliable transmission and distribution of power is ensured by these devices, which perform several activities such as voltage alteration, circuit interruption or connection, measurement of high-voltage current and voltage, and protection against lightning overvoltage. Quantifying the present status of these equipment by testing as well as online monitoring is the main emphasis of substation state assessment.

In order to ascertain whether or not an item is suitable for use in the system, electrical testing procedures examine its insulation and functioning. The most common approach compares the results of the test at the moment of the equipment's delivery to those from the manufacturer-specified ranges or from earlier measurements. Equipment condition is determined by analyzing post-test departures from these reference values and consulting with experts. In order to gather equipment characteristics in real-time, online monitoring makes use of a variety of sensors. A monitoring system receives the data and either human analysts or computer programs evaluate it. Various equipment in a substation may have their online monitoring data integrated by specialist modules in the Supervisory Control and Data Acquisition system. Insulation monitoring systems, gas chromatography results, winding and oil temperatures, current and voltage readings, and data from current and voltage transformers are all part of the data collected by transformers for monitoring purposes. Position sensors record the number and status of switch operations; temperature sensors record the temperature, and current transformers record the running current as part of the data set for monitoring switchgear. The data collected by temperature sensors, humidity sensors, and specialized monitoring devices for switchgear cabinets includes both interior and exterior temperatures, relative humidity, and partial discharge. In order to evaluate the effectiveness of the lightning arrester, data is collected by a leakage current tester. Additionally, operational conduction events may be tracked by using a discharge counter to record the frequency of discharges. Using temperature sensors, capacitor monitoring mainly focuses on the capacitors' and their peripheral devices' temperatures. Partially discharged cables, as well as their sheath and interior temperatures, are among the data points collected by cable monitoring systems.

In order to transfer electricity from a source to many loads over long distances at high voltages and currents, systems for distribution and transmission are crucial. Therefore, it is critical to monitor and regulate the different parts of these structures. Coils, clamps, or instruments with transformers were used to detect just the grid voltage and current characteristics in the past for this purpose. But their cumbersome designs make them substation-only, and the fact that they come into direct touch with high-voltage cables makes installation and maintenance a pain. A number of changes are taking place inside the power grid at the moment, such as the integration of renewable energy sources, the introduction of bidirectional power flow, automation and remote control, and so on. These advancements need small, energy-efficient sensors that can detect a broad range of grid factors, including data on magnetic fields, temperatures, humidity, acoustics, and more. This will allow for predictive management of the power grid as well as real-time monitoring over large areas. Among the many parts of the electrical power grid's outage management system, sensors are now considered crucial. Sensors' capacity to monitor networks for transmission and distribution in real time aids in either preventing interruptions entirely or mitigating their effects. The electrical grid may now undergo condition-based maintenance, which, in certain instances, can be more efficient and cost-effective than the usual planned maintenance, all thanks to sensors. Due to their exclusive responsibility for acquiring raw fault data, sensors also constitute a very important input facing component for the majority of monitoring and control systems. When it comes to analyzing the nature of the instruments' working and breakdown in the transmission as well as distribution lines, it is crucial to classify and forecast various grid metrics received from the sensors. This will allow for better predictive, adaptive, along with corrective analysis. Probabilistic risk assessment and contingency

assessments using sensors greatly enhance power grid asset usage.

2.4 Sensors for safety supervision

A number of critical components of the transmission and distribution networks have made use of sensors. These components include: substations, power transformers, insulators, lightning arrestors, transmission line equipment, underground cables, power transformers, circuit breakers, battery systems, and transmission while distribution line poles. In a SCADA (supervisory control and data acquisition) system, sensors are an integral component of the input facing parts of the remote terminal units with phase measuring units. The power grid relies on accurate and discrete sensors for a number of tasks, including monitoring equipment operating temperatures, measuring rated and leakage waves, and improving distribution and transmission line monitoring using acoustic sensing. Power conductors, Insulators, power transformers, breakers, and various other parts of the power system have a variety of sensors installed, including magnetic, vibrational, acoustic, fiber optic, infrared ray, and so on.

Below is a summary of some of the most important parts of the power grid's transmission and distribution systems, along with some of the most common problems that might arise with them. There has been an explanation of the various sensors and how they work to reduce these errors.

2.5 Power transformers

The most important and costly part of a substation is the power transformer. Their primary function is to reduce the high voltages of the transmission lines to levels suitable for sub-transmission and distribution. Although power transformers are durable and can last for 60 years with proper care and safety features like surge arresters, they are still prone to a number of failures and breakdowns while in use. These can range from a rise in transmission losses to the transformer's total failure, which can cause fires and other dangers and cost millions of dollars and lives. The components of power transformers wear down over time, which is a common source of damage. Damage to the transformer may also occur via insulation deterioration, oil leakage, or oil absorption by moisture. A power transformer's functionality may also be significantly compromised by lightning, seismic activity, and line surges. Several sensors have been installed on the power transformer to keep an eye on these problems.

2.6 Overhead line power conductors

Power transmission across vast distances relies on overhead line power cables, which are vulnerable to corrosion caused by extreme weather and high voltages. Both the transmission and distribution systems rely on overhead line power wires. The following are some of the reasons why this degradation occurred. As a result of air pollution, conductor deterioration is a typical side effect of galvanization. Severe mechanical stress is placed on the power conductors by vibration damage, which includes aeolian vibration, galloping, and sub conductor oscillations. Damage to the electrical wires, including sagging and breakage, may occur as a result of extreme weather events such strong winds, rain, and snow.

2.7 Overhead line insulators

Among the primary roles of overhead line insulators is to provide a highly resistant channel for leakage currents and to fortify the power conductors mechanically so that they can endure external loads. There are many different kinds of insulators, but the most common ones are pin, suspension, strain, shackle, disc, stay, and other similar types. In the event of a flashover, insulators may be punctured or deteriorated as a result of age, mechanical stress, electrical stress, or air contaminants, all of which can induce dielectric breakdown. Horizontal transmission line insulators have been the target of many sensor deployments in an effort to detect and document the aforementioned breakdowns.

2.8 Distribution system switchgears & protective devices

Circuit breakers, reclosers, relays, fuses, sectionalizers, and other protective devices safeguard the power transformers, power conductors, and distribution side equipment against fault currents and high voltages in the distribution system. The protection mechanisms are often impacted by fault currents, which may cause sympathetic tripping, shorten the effectiveness of distance relays, disrupt relay coordination, and more. Finding faulty parts of line used to be done using faulted circuit indicators. Defected segments of the line served as indicators of the fault level. A mechanical target, such as a flag or an LED, was put up to show the problem level. Nevertheless, the time it takes to clear faults is prolonged since this process is sluggish and causes a delay in the communication among protective devices like reclosers and downstream devices like fuses or other reclosers.

2.9 Transmission line towers

Transmission towers provide ground resistance, house a variety of power conversion, safeguards, and insulation devices, and ensure the continued operation of transmission line power conductors, making them an essential component of the electrical grid. Because of their size and complexity, transmission towers are vulnerable to shifting, tilting, cracking, vibrations, along with subsidence. These concerns may lead to serious complications, including as communication network and transmission line disruptions, galloping transmission lines, settlement tilt in the tower, and even tower or conductor collapse.

2.10 Underground cables

Due to the increased dependability, stability, security, and safety that subterranean cables provide to the grid as a whole, they are quickly replacing overhead lines. Subterranean cables may be used in both the transmission and distribution networks. While burying the cables lowers the outage risk, they are nevertheless susceptible to catastrophic defects caused by partial discharge, temperature increases, cable aging, wear and tear, etc. As a result, finding and fixing cable faults is a challenging and costly ordeal. Because of this, a wide range of sensors have been created and used for identifying faults and monitoring in subterranean cables.

3 Related work

Importantly, the goal of the researchers in [14] is to decrease energy consumption and increase the dependability of electrical equipment at substations. Substation safety and stability are ensured by the AC along with DC systems used in substations. At that time, the station electrical infrastructure does not have an intelligent way to track the status of different pieces of equipment, their energy efficiency, or to alert operators to anything out of the ordinary. The integration of measuring and sensing technologies, big data applications, with artificial intelligence forms the basis of that article's monitoring technology. The system uses feature matching, recognize patterns, while machine learning to extract electrical characteristic parameters from all electrical equipment in the station. It then identifies and detects the type of equipment, its electrical information, when it is operating, its status, and indicators of energy consumption. That greatly enhances the substation safety management level by allowing holographic visual awareness of the station's electrical system's load equipment.

In order to address the safety monitoring situation, the authors of [15] suggested a hybrid routing technique that takes into account the priority of services and is wirelessly self-organizing. At the outset, they have a look at the possible outcomes of data exchange between safety monitoring equipment installed at substation and transmission sites. Next, the procedures for implementing a hybrid data routing technique that takes service priority into account are detailed. Lastly, a typical wireless self-organized networks scenario is used to verify the effectiveness of the proposed architecture. The experimental findings show that the suggested routing technique fulfills the delay QoS criteria for various priority services while minimizing transmission energy usage.

An approach to monitoring diagram verification was developed by the authors of the aforementioned article [16]. That method is based on the analysis and verification of wiring diagrams. The authors further enhanced the automatic approval logic for the entire monitoring process, from the slave end to the develop end, and then put it to use in real-world engineering applications.

A cloud-based model while improved evidence theory-based risk assessment approach for substation power surveillance systems is proposed by the experimenters of [17] to address the issues of inadequate system modeling, unclear expert evaluation opinions, and failure to take the system-wide risk into account when assessing such systems. First, the substation power monitoring system's structure and security requirements are taken into account when analyzing the system's equipment, security objectives, and threats. Then, the overall risk assessment framework for the system is established. The optimal combination assignment is then implemented using the FAHP while the modified entropy weight method. The substation power monitoring system's risk level is determined after a thorough evaluation using the cloud model and better evidence theory. The monitoring system's safety management offers a fresh perspective.

With the use of early warning and monitoring, the authors of [18] ensure that substation maintenance workers and construction workers are protected while on the job. First, the article compiles employee image data and captures images of personnel using monitoring equipment like intelligent cameras to create an image sample library. Second, the upkeep and operation of detection model is built using the HOG algorithm, CNN, and image processing algorithms. The system's accuracy is enhanced by exporting personnel images to facial recognition, intelligent detection models for safety helmets, and clothing. That enables the tracking of personnel who enter and exit the substation, and the data and intelligence level of substations safety control are effectively enhanced.

In order to tackle issues including breakdowns of equipment, energy losses, and security concerns, the

researchers in [19] developed a power substation monitoring and automated control system that is based on the IoT. The system gathers real-time data on voltage, current, along with temperature from different substation components via a network of sensors. After data collection is complete, it is sent to an approved control center via an intuitive Blynk IoT app. Proactive maintenance is made possible by the use of advanced analytics and algorithms, which can detect any issues and start activities immediately. Furthermore, by keeping an eye on voltage levels as well as balancing loads, the system makes the most of available resources. Better accessibility and faster reactions to critical events are made possible by integration with the Blynk app, which allows for remote monitoring, real-time notifications, and remote-control capabilities. The results demonstrate that the suggested method enhances the substation's efficiency, reduces downtime, and boosts grid dependability, leading to a more sustainable and robust electricity infrastructure.

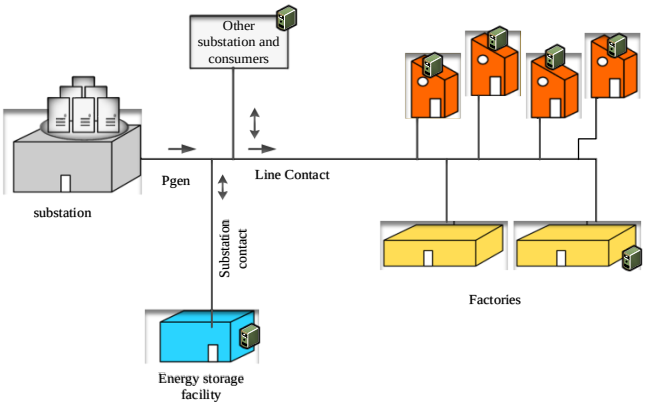


Figure1: Substation monitoring

By integrating IoT sensor networks with fuzzy logic, a Fuzzy Inference-Based Safety Monitoring Framework may provide a sophisticated and astute method of risk evaluation for substation power operations. With the complicated electrical environment comes inherent uncertainties, and this system goes beyond basic alarm triggers to address them.

3.1 Role of IoT sensor networks

By collecting detailed information in real-time from key locations within the substation, the Internet of Things sensor network lays the groundwork for the framework. In order to keep tabs on things like transformers, circuit breakers, and busbar temperatures, these networks may use a variety of sensors.

- Equipment vibration detectors for early mechanical failure detection

4 Proposed work

4.1 Research idea

One common method of substation management today is the intelligent simulation system. In order to determine how to maximize the substation intelligent simulation system's safety using an improved genetic algorithm, this research investigates the safety operation analysis of such a system. This article found that data from substation intelligent simulation platforms based on improved genetic computations is better than data from traditional substation intelligent simulation systems. This proves that improved genetic techniques may enhance the security of substation intelligent simulations systems. The testing involved comparing the number of vulnerabilities discovered while the number of illegal intrusions in the two systems, which is given in fig 1.

- Acoustic sensors to detect any abnormal noises that might be signs of a developing problem
- Humidity, gas (such as SF6 gas leaks), and air quality sensors for use in environmental settings
- Electrical devices that can measure power, current, and voltage

The substation's operational health is comprehensively monitored in real-time by continually collecting and wirelessly transmitting this data to a central processing unit or a cloud platform. An IoT sensor network gathers real-time data, and fuzzy logic offers a sophisticated, intelligent method of risk assessment in a Fuzzy Inference-Based Safety Monitoring Framework for substation power operations. Rather than a static file, this framework's dataset is a real-time feed from a number of sensors.

a. Dataset from IoT Sensor Networks

A time-series compilation of data points from different sensors placed throughout the substation constitutes the dataset for this architecture. It is an ever-evolving dataset that is alive and well. This dataset contains important variables such as:

- Electrical Parameters: Power (kW), Frequency (Hz), Current (A), and Voltage (V). These are the most basic signs of the stability and load on the substation.
- Thermal Parameters: The temperature, in degrees Celsius, of essential parts including busbars, circuit breakers, and transformers. When anything starts to overheat, it's usually a sign that something is wrong.
- Environmental Factors: Humidity, temperature, and gas levels (such as SF6 in the event of a

leak). Both the functionality and security of electrical appliances might be compromised by these.

4.2 Data preprocessing

The dataset represents a power transformer's simulated operational data set spanning a decade, including both typical and out-of-the-ordinary working scenarios. Time stamps and anomaly labels are attached to each record. In brief, the following are some of the many electrical, thermal, chemical, along with frequency response characteristics captured by the measured variables:

- Currents and voltages, both primary and secondary, as measured electrically ($V_{prim\ mms}$, $V_{suc.ms}$, $I_{prim.ms}$, $I_{sec.ms}$).
- Oil temperature and room temperature are the thermal parameters (T_{cal} , T_{eav}).
- Hydrogen concentrations in oil-dissolved gases (H_2), methane (CH_4), acetylene (C_2H_2), besides carbon monoxide (CO), stated in ppm.
- FRA (frequency response analysis): tangent delta, capacitance, and impedance magnitude and phase (C_p, $|z|$, $\angle Z$, TgD) assessed using four different bands of frequencies ($100\ \text{Hz} - 1\text{kHz}, 1\text{kHz} - 10\text{kHz}, 10\text{kHz} - 100\text{kHz}, 100\text{kHz} - 1\ \text{MHz}$).
- FRA in action (FRACTIVE): identical set of FRA characteristics assessed independently on stages A, B, and C.

The dataset has about 60 descriptive characteristics in total, in addition to the columns for timestamps and anomalies. By excluding the timestamp and anomaly, we were able to generate the feature matrix X. To guarantee that each feature had a zero mean with unit variance, we used Z-score normalization:

$$z_i = \frac{x_i - \mu}{\sigma} \quad (1)$$

where x_i σ is the standard deviation, μ represents the mean, and is a feature value.

4.3 Dimensionality reduction

Principal Component Analysis (PCA) was used to reduce computational cost and duplication among strongly connected data. A minimum of 20% of the overall variance was maintained by selecting a number of retained parts k such that:

$$\sum_{i=1}^{k} \lambda_i \geq 0.20 \quad (2)$$

- Mechanical Parameters: Data on vibration and sound to identify mechanical wear and arcing in its early stages

where λ_i stands for the covariance matrix's i-th eigenvalue. Finding a happy medium between computing efficiency and model correctness led to the selection of this criterion. Processing the whole set of features would greatly raise training cost because to the high number of monitored variables. Thus, in order to expedite learning while preserving representative data, this research used an arbitrary variance retention of 20%. You should know that this decision is case-specific; other uses could call for a different retention percentage. The resultant matrix of reduced features $X_{PCA} \in R^{n \times k}$ before being categorized.

By obtaining the mean of each row in the training sample matrix and subtracting it from each feature value in that row, we can create an additional two-dimensional feature matrix, which standardizes the overall sample matrix. The testing method also requires a standardization procedure for the test sample's feature vectors,

$$x_{v^*} = x_{v_i} - \overline{x_{iq}} \quad (3)$$

where $\overline{x_{ij}} = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$. We compute the covariance matrix of the training sample's new feature matrix. The covariance matrix's eigenvalues and eigenvectors are computed, with the eigenvalues ordered from most to least significant. In the findings and discussion portion of this study, we will compute and analyze the eigenvalue contribution. Dimension reduction as well as performance comparison may be facilitated by obtaining alternative projection matrices of the ideal projection axis, which are created by choosing different eigenvector sequence lengths in a large-to-small order.

The projection matrix is used to project the features of each 1 s data set (training sample, test sample) after standardization. The result is a new set of features for both the training and testing samples, which can be adjusted to achieve different dimensional reduction effects by choosing different eigenvector sequence lengths.

When the electrical grid is running smoothly or has a three-phase fault, the asymmetrical fault initiating requirement is not fulfilled since the zero-sequence and negative-sequence currents are almost nonexistent. Here, we use the blocking criteria of low-order harmonic excitation current and use the current magnitude ratio criterion to get the conclusion. The outcome of an asymmetrical grid fault is dictated by both the current magnitude criteria with the low-order harmonic excitation current requirement in tandem. One must first measure the transient current at the grounding point of the N line in

order to determine the amplitude of the lower-order harmonic elements. The ground fault among the two neutral locations is then detected after identifying the low-order harmonic current excitation criteria.

4.4 Fuzzy reasoning model

Regular inspections via operation and maintenance staff are necessary because the substation environment effects interior equipment. Aside from automated monitoring, these inspections cover topics like checking the temperature at contact while wire connection points, checking the integrity of aluminum stranded wire, evaluating the interference caused by plants or animals, checking the oil level in oil-filled devices, and monitoring the gas pressure of SF6 equipment.

- Noise pollution, electromagnetic field exposure, and aesthetics are all important environmental factors that must be considered while designing a substation. Substations may be designed and landscaped to fit in with their surroundings.

The decision-making layer takes fire likelihood into account while making judgments, along with other criteria. There can be no way to tell whether a fire is happening when the probability is precisely 0.5. In order to enhance the degree of decision-making, the length of the fire signal is included as a decision-making component, and fuzzy theory is then applied. There are four tiers to the decision-making level's output: no fire, warning, alarm, and severe alarm. First, the input and output signals are fuzzified in the fuzzy reasoning phase. Then, the fuzzy rules are established. Interim relationship between fuzzy sets is defined by equation (4). For a fuzzy implication relationship R, rule i is the corresponding rule. The last step is to create the input/output rules table.

$$R_i = (Y_1(i) \text{ and } Y_2(i) \text{ and } \mathrm{T}_i)$$
$$R(x, y, z, u) = U_{i=1}^{n} R_i \qquad (4)$$

The developed fuzzy inference system's output surface is shown in Table 2 and Table 3.

Fuzzy rules example

1. IF **Temperature** is High AND **Humidity** is Wet THEN **Safety Index** is Danger
2. IF **Voltage** is Stable AND **Gas Level** is Safe THEN **Safety Index** is Safe
3. IF **Personnel** is Present AND **Gas Level** is Warning THEN **Safety Index** is Caution

Table 2: Fuzzy input variables

Variable	**Range**	**Membership Functions**
Temperature	0–100°C	Low, Normal, High
Voltage	0–500V	Stable, Fluctuating, Overload
Gas Level	0–100 ppm	Safe, Warning, Critical
Personnel Presence	0–1 (binary or probability)	None, Present
Humidity	0–100%	Dry, Moderate, Wet

Table 3: Output variable

Output	**Range**	**Categories**
Safety Index	0–100	Safe, Caution, Danger

Membership function

At its core, the concept of a fuzzy set includes the membership function (x). It finds out how much of a fuzzy set member a certain element is. Depending on the problem's context, the choice of a suitable function for membership is often subjective. The singleton, triangle, trapezoidal, and Gaussian shapes among the most popular choices for functions related to membership. The suggested method defines the input and output variables' membership functions using a trapezoidal membership function. Energy consumption ($E\mathbf{O}$) is the only output of this system. Despite the convenience of the triangle membership structure, the research's key parameters—which include temperature, set-points, price, and humidity—are best described using the trapezoidal membership function because these variables do not exhibit abrupt changes in value and tend to stay constant over extended periods of time. Therefore, the simplicity of these flattened line membership processes is a benefit.

Algorithm for Fuzzy Logic
Step 1: Providing the scope of membership functions and setting the input and output variables.
Step 2: Input value is outputted with an alternate membership degree [0, 1] once the membership functions are defined as the fuzzy processing software.
Step 3:

We are creating a fuzzy rules foundation. The semantic transform of "IF X1 is A AND X2 is B, THEN Y is C" is used by designers to build a fuzzy rule base which will serve as the basis of the fuzzy inference engine. This base is based on experience or knowledge from experts.

Step 4:

Using an interactive fuzzy operation management rule basis, the outcomes are produced by fuzzyification inference

Step 5:

Defuzzification: It used a membership of degrees to aggregate the results and get an output value.

The process of establishing rules in a system becomes more tedious as the number of rules needs to be established grows. A lot of methods have been developed to make rule definition easier. This research proposes a mechanism based on combinatorics and weightage for the automated development of rule bases. As seen in Algorithm 1, $Score$ is computed by assigning a weightage to each membership associated with a single input parameter. This weightage is then utilized to assign values to the resultant variables. The following are the main FLC procedures: The initialization and definition of all member functions of the system characteristics takes place during the fuzzification process, which is the first phase. Step two involves selecting an appropriate output fuzzy value and establishing the rules in the rule base by adding weights to the membership functions of the input parameters. Step three involves assessing energy use with the help of the Mamdani FIS and the Sugeno FIS. To achieve a clear number for the energy usage, defuzzification is done after the rule assessment. The last step is to compute the remaining performance metrics.

After the membership functions of the input parameters are weighted in the second stage, we add a parameter $Scofe$ to indicate energy consumption and avoid the combinatorial expansion of IF-THEN rules. When $Scoae$ is low, energy usage is also low. To get the $Tcofe$, we add up the weights given to the variables' membership functions. Low, medium, and high membership functions are represented by 0, 1, and 2 weights, respectively, in the weight system.

Occupancy constitutes the only exception; it indicates if there are any tenants in the building and has a binary value of 0 or 1. When $Tcofe$ is computed by summing the weightings of membership functions for the the parameters being input, the approach utilized for automated rule generation uses a combination of these parameters, where order is irrelevant, and they adhere to the commutative property. Here is the $Scofe$ at any given time:

$$Score = \sum_{i=1}^{16} W(vi) \qquad (5)$$

where W is weight and vi are the variables.

4.5 Substation failure control strategy

The failure alarm host communicates with the failure suppression system to implement appropriate failure suppression procedures according to the decision-making evaluation of the estimated sample failure probability value. The substation runs smoothly when there's no failure; when there's a warning, the failure extinguishing gadget isn't turned on, but the substation staff keeps an eye out for unusual signals and goes to the warning location if needed; when there's an alarm, the failure alarm host gets the signal to turn on the apparatus immediately; and when there's a serious alarm, the apparatus is turned on immediately, the power is turned off, and the substation staff responds to the accident. The failure alarm host communicates with the failure suppression system to implement appropriate failure suppression procedures according to the decision-making evaluation of the estimated sample failure probability value. The substation runs smoothly when there's no failure; when there's a warning, the failure extinguishing gadget isn't turned on, but the substation staff keeps an eye out for unusual signals and goes to the warning location if needed; when there's an alarm, the failure alarm host gets the signal to turn on the apparatus immediately; and when there's a serious alarm, the apparatus is turned on immediately, the power is turned off, and the substation staff responds to the accident.

4.6 Input signal correlates with an output signal

In the text, the input signal is set to where i=1, 2,…,n. The output signal is set to j=1, 2…, m. This is the connection between them:

$$\begin{aligned} S_k &= \sum_{i=1}^{\pi} v_{ki} X_i + v_{k0,} 1 \le k \le h \\ Z_k &= \sigma(S_k), 1 \le k \le h \\ Y_i &= \sum_{k=1}^{n} \omega_k Z_k + \omega_{p,1} \le j \le m \end{aligned} \qquad (6)$$

The hidden layer input is S_k, the hidden layer output is Z_k, v_k the weight of the connection between the input and hidden layers, the threshold of the hidden layer, the weight of the connection between the hidden and output layers, and the output layer threshold are all represented by v_{ki} and ü_0, respectively.

To determine the error, we simulate the output of the training samples. Then, we update the weights and thresholds to match the error criteria by propagating the error backwards. With the error function:

$$E = \frac{1}{2}\sum_{k=1}^{t} \sum_{k=1}^{m} \left(q_k^l - p_k^d\right)^2 \qquad (7)$$

5 Results & discussion

5.1 Implementation

We measured the root-mean-square current dimensions for the breaker in the protective relays and modeled the electrical fault currents in MATLAB/Simulink.

(i). Assessment indicators

The paper uses two error indices—the root means square error (RMSE) and the mean absolute percentage error (yMAPE)—to assess the accuracy of the substation failure warning model. The MAPE and RMSE metrics assess the model's precision. The MAPE equation is in () while the RMSE equation is in (8).

$$y_{\text{MAPE}} = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_a(i) - y_p(i)}{y_a(i)}\right| \qquad (8)$$

$$y_{\text{RMSK}} = \sqrt{\frac{\sum_{i=1}^{n} \left[y_a(i) - y_p(i)\right]^2}{n}} \qquad (9)$$

$y_s(i)$ and $y_p(i)$ are the current and projected probabilities of failure.

5.2 Accuracy of measured current and voltage

The % errors for both voltage and current measured on the RTS and HMI were computed applying the measured phases currents and voltages for the power meters and protection relays. Equation (10) was used to determine the percentage inaccuracy of the observed currents ($E_{\%}$ in) in phase A, B, or C.

$$E_{\%}\ /\text{In} = \frac{I_{nWMI} - I_n\ \text{FTS}}{I_n\ \text{KTS}} \times 100 \quad (10)$$

where I_nRTS which is the n(" "A," "B," or "C") phase current measured in amperes from the RTS, and I_n HMI which is the n(" "A," "B," or "C) phase current measured in amperes from the HMI of the IEDs.

We used Equation (9). to get the percentage error for the observed n(" "A," " B, or C) the phase voltages ($E_{\%}$ 〚" " V_n) in which V_n RTS is the $n(A, B$, or $C)$ phase voltage collected from the RTS in volts, and $V_n n_{HM}$ is the $n(A, B$, or C) phase voltage collected from the IEDs' HMI in volts.

Table 4: The system monitored variables.

Parameter	Busbars	Generators	Dynamic Loads	ML Model
Frequency		X	X	√
Rotor Angle		X		√
Angular Speed		X		√
Torque		X		√
Voltage	X	X	X	√
Power Factor	X	X	X	√
Apparent Power	X	X	X	√
Active Power	X	X	X	√
Current	X	X	X	√
Reactive Power	X	X	X	√

This study two options when using a generator: lock mode and free mode. When locked into lock mode, the generators produce electricity in direct proportion to the speed of rotation of the primary mover. When operating in free method, the generator responds to mechanical torque. The sound frequency in the generators may be measured by observing its angular velocity, which varies with its load, which is given in Table 5.

Table 5: Simulation parameter

Parameter	Values
Conductor radius r_c (mm)	14.68
Insulation radius r_{in} (mm)	18.22
Sheath radius r_s (mm)	20.96
Line length L (m)	600
Effective resistance R_e (Ω/km)	0.56
Distributed capacitance C_d (μF/km)	0.529
Ground resistor R_G (Ω)	5
Supply voltage U (V)	390 (RMS)
Frequency f (Hz)	60

5.3 Comparison and analysis of effectiveness

We utilized data from a variety of sources linked to the primary transformer, including online surveillance, testing, maintenance, and operation, and environmental conditions, to evaluate the performance of the suggested approach for assessing the quality of electrical equipment with previous classifier algorithms. After that, we used 70% of the dataset for training and 30% for testing

purposes, using the steps outlined in (1), to evaluate the electrical equipment's quality. Then, we used a number of performance measures to forecast the primary transformer outcomes, including accuracy, recall, precision, F1-score, the (ROC curve, as well as AUC, and we compared our method's efficacy with other classifier algorithms, which is given in Table 6.

Table 6: Performance metrics for each method

Classifiers	State	Accuracy	Precision	Recall	F1-Score
This method	Normal	92.06%	87.04%	93.28%	85.16%
	Suspicious	95.20%	87.30%	87.70%	86.70%
	Abnormal	98.22%	97.18%	93.44%	94.79%
FAHP	Normal	94.11%	86.94%	91.37%	87.12%
	Suspicious	90.23%	89.14%	83.72%	83.96%
	Abnormal	97.13%	99.14%	94.70%	99.71%
HOG	Normal	92.45%	93.33%	83.11%	86.59%
	Suspicious	90.83%	81.78%	89.86%	86.91%
	Abnormal	99.86%	93.73%	93.78%	95.60%

In both the normal and attention phases, the suggested technique shows better categorization performance. Its accuracy and recall for aberrant states are better than the HOG and FAHP models, but its performance is somewhat worse overall. Increases in AUC and improvements to the ROC curves demonstrating decreased FPR and increased TPR are indicators of the method's better performance. The dependability of electrical equipment may be evaluated and choices about shutdown, examination, or maintenance needs can be informed by this performance.

6 Conclusion

When it comes to addressing operational dangers at substation power plants, the Fuzzy Inference-Based Safety Monitoring Framework leveraging IoT sensor networks provides a robust, interpretable, and powerful solution. This framework improves productivity and safety in complicated, ever-changing situations by integrating fuzzy logic's reasoning capabilities with the IoT sensors' real-time awareness. Problems arise due to the multi-factor influence and complexity of data pertaining to electrical equipment status monitoring. Computing association rules becomes more complicated as datasets expand due to the exponential growth in the total amount of candidate itemset. Addressing these highlighted problems will be the focus of future research as we refine the framework for applications in various and complicated situations. Finally, this technique shows a lot of promise and is useful for assessing the condition of substations' high-voltage electrical equipment.

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Optimization of Electric Vehicle Charging Routes Using Fuzzy Inference and Enhanced Gray Wolf Algorithm

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Electric vehicles (EVs) help lower carbon emissions but face challenges from varied charging prices and long wait times. This study optimizes EV charging route planning to minimize user costs under diverse pricing and diverse driver preferences. Vague user preferences are converted into explicit weightings by employing a fuzzy inference system, and a total cost function covering economic, time, and carbon costs is defined. The optimal charging route is then determined by applying Depth-First Search combined with the Enhanced Gray Wolf Algorithm (EGWA). The method is tested on a single EV and a cluster of EVs. The results demonstrate that the combination of EGWA and fuzzy inference system can select the most compliant charging path for the user, thus effectively reducing the user's cost. Tests on single EV show EGWA consistently achieves the lowest comprehensive cost across weight combinations. Specifically, EGWA lowers costs by 12.47% on average compared to GWO, 9.27% over IWOA, and 5.08% over LPGA. EGWA also demonstrates faster convergence and better stability. These results highlight the benefit of integrating fuzzy modeling with metaheuristic optimization to support drivers in choosing cost-effective and environmentally friendly routes. The proposed method provides practical guidance for intelligent EV route planning systems.

Povzetek: Optimizacija poti polnjenja električnih vozil je izvedena z uporabo mehke logike za modeliranje preferenc uporabnikov in izboljšanega algoritma sivega volka. Metoda učinkovito zmanjša skupne stroške (ekonomske, časovne in okoljske) ter kaže hitro konvergenco in stabilnost.

1 Introduction

After the industrial revolution, the excessive carbon dioxide generated by the burning of a large number of fossil energy sources caused great negative effects on the earth [1]. To mitigate the environmental crisis, various countries have proposed carbon neutrality schedules that align with their national conditions to promote the implementation of energy conservation and emission reduction policies. All sectors are adopting certain measures in response to environmental protection policies. Among these, the issue of green vehicle routing in the transportation industry considers environmental factors from the perspectives of vehicles and logistic. Green vehicle routing problem (GVRP) includes GVRP for traditional fossil fuel vehicles, GVRP for alternative fuel vehicles and GVRP for hybrid vehicles [2]. With the development of lithium battery technology, the deployment and application of alternative fuel vehicles—namely electric vehicles (EVs)—have accelerated. And charging facilities have also become widespread [3].

The charging tariffs of charging stations are affected by a variety of factors [4], with different tariffs for the same charging station at different times, and different charging tariffs for different charging stations at the same time. Due to the battery characteristics of EVs, charging time is consumed for a long time [5]. As the number of EVs grows year after year [6], more vehicles use charging facilities and charging waiting time grows gradually. Economic cost and time cost become important factors affecting the charging route planning of EVs. To respond to the environmental protection policy, carbon emission should also be included in the consideration of route planning. How to carry out route planning according to drivers' needs has become the focus of research.

Most users' cost requirements cannot be accurately converted into specific values. Users' requirements cannot be directly entered into the optimization system. Moreover, the individual user's demand for the different costs is independent, and different users' demands for the costs are diverse, which increases the difficulty of charging path optimization. In order to address the diverse charging needs of users, it is decided to use a fuzzy inference system to convert user needs into weights. Fuzzy inference is a reasoning method based on fuzzy set theory to deal with uncertainty and ambiguity [7]. Fuzzy inference systems can be used to assist in autonomous driving technology [8]. The fuzzy inference system can also control EV charging and discharging based on the State of Charge (SOC) and the stay time of EV parked in

the parking lot [9-10]. The new method combining hesitant fuzzy sets and multiplicative preference relations converts linguistic terms into hesitant fuzzy multiplicative elements to each criterion weight [11].

About economic costs, most studies on charging route planning consider time-of-use (TOU) charging pricing at charging stations [12]. For the Traveling Salesman Problem (TSP), Yang *et al.* [13] introduced a model for fast and scheduled charging of vehicles under TOU pricing. For cluster problems, a bi-level optimization model can also be utilized, which considers charging prices under TOU pricing [14]. However, none of this literature considers the different charging prices at different charging stations at the same time. The game between charging price and charging distance is also an important factor affecting the economic cost and time cost.

About time costs, Schoenberg *et al.* [5] propose a centralized database for route selection using mathematical methods to predict the waiting time in advance. Tan *et al.* [15] consider time-perceived fairness and waiting time, then propose a time-perceived fairness index. Literatures use either mathematical methods or heuristic algorithms to calculate. However, both methods have their advantages and disadvantages.

About carbon emission costs, Qiao *et al.* [16] proposed an operational model of coupled electricity-transportation network to achieve the goals of cost reduction and low carbon emissions while minimizing the self-consumption of each entity.

Mathematical methods, although straightforward, are complex to handle and require simplifying constraints to solve the problem [17-21]. The cooperative transportation network and distribution network scheduling method is designed which utilizes the combined distributed biased minimum consistency algorithm and the generalized Benders decomposition algorithm [22].

Heuristic algorithms are simple and easy to understand. However, heuristic algorithms usually find an approximate solution rather than an optimal solution within a certain period and they do not guarantee consistency of results [23]. The conventional algorithm requires extensive computation [24], necessitating improvements over traditional methods [25-32]. Deep learning algorithms can personalize travel routes, with the multi-objective shortest path approximation and single-objective average achievement rate both exceeding 93.36% [33]. The average charging cost of the path optimization model based on the improved topology and ant algorithm is 7%–26% lower than that of other models [34].

To fill the gap in the above literatures, the paper proposes the Enhanced Gray Wolf Algorithm (EGWA) with the fuzzy inference combined for solving the charging route optimization problem with different user demands when there are multiple charging stations with different charging prices. The core idea is to transform the fuzzy and independent diversified needs of users into the weights of the objective function for path finding optimization through fuzzy reasoning. EGWA is utilized to find the optimal charging path. The main contributions of this paper are two:

(1) A model for calculating the weights of the objective function using a fuzzy inference system is developed to convert the economic cost, time cost and carbon emission cost demands of the users, which cannot be accurately expressed in numbers when facing charging, into precise weight numbers to satisfy the different charging cost demands of the users.

(2) In order to improve the late convergence speed and solve the shortcomings of the traditional gray wolf optimization algorithm which is easy to fall into the local optimum, 2-opt and roulette wheel selection are combined with the traditional GWO to find the charging path with the lowest comprehensive cost to satisfy the users' needs.

The remainder of the paper is organized as follows. Section II establishes the model for EV route optimization. Section III describes the principles and improvements of algorithms. Section IV presents two case studies involving optimization. Section V provides a conclusion of the work.

2 System model

The charging price of EV charging stations is affected by many factors, the most important of which are energy cost, equipment investment and operation cost [35]. The charging price of each charging station is different, and the needs of users are different. Choosing the charging station that best meets the driver's needs becomes a necessary consideration.

According to its SOC, the EV charging route planning problem can be divided into the following two categories.

1) When the remaining charge of an EV is less than a certain value of the total charge, it is necessary to avoid a situation in which the charge runs out and travel is affected. In this case, the vehicle should immediately find the nearest charging station to its current location and plan the shortest route to the charging station.

2) When the remaining charge of an EV is more than the certain value of its total charge, there are more charging stations to choose from. By comparing factors such as the charging price, waiting time and charging time, the most cost-effective charging route that meets the charging needs can be identified.

It is shown that N represents the traffic road nodes on the map. $N_{ch} \subset N$ represents the nodes of EV charging stations, where EVs can stay and complete charging tasks. The route from node i to node j is denoted as $(i,j) \in P$, and P is the set of all feasible routes.

The shortest charging route planning for EVs is to find the shortest route to the charging station with an objective function of

$$F_{dis}^{N_{ch}} = \sum_{(i,j)\in P} x_{ij,t} d_{ij} \tag{1}$$

where $x_{ij,t}$ indicates whether the EV passes through (i,j) at period of t . d_{ij} represents the distance from node i to node j (unit: km). If the route planning of the EV includes traveling from node i to node j, then $x_{ij}=1$; otherwise, $x_{ij}=0$. Eq.(1) represents the distance from the starting node to charging station N_{ch}.

The cost of charging an EV includes the economic cost, the time cost and the carbon emission cost. The current EV charging technology initially follows a constant current charging mode and switches to a constant voltage charging mode once a certain amount of charge is reached, with the former mode being faster and the latter slower and more time-consuming. To give due consideration to charging efficiency and maximize time savings, it is assumed that charging at the charging station will stop once the EV's battery reaches 80%. The economic cost refers to the expenses incurred at different charging stations. The time cost includes both charging time and waiting time. Electricity is a kind of clean energy, and the carbon emission of EVs when consuming electricity is small and negligible. During the use of EVs, the main carbon emissions are concentrated in the charging process. And the carbon emission in the charging process mainly depends on the energy structure of the local power grid. For the generality of the carbon emission index, the unit carbon emission is taken as 0.9kg/kWh [36]. The formulas are as follows:

$$Q_f = 80\%Q \tag{2}$$

$$F_{pr}^{N_{ch}} = (Q_f - e_{ch}) \times M_{N_{ch}} \tag{3}$$

$$F_{n_s,n_e}^{N_{ch}} = \sum_{(i,j)\in P} \frac{d_{ij}}{v_{ij}} x_{ij} + \frac{Q_f - e_{ch}}{P_{ch}} \tag{4}$$

$$F_{em}^{N_{ch}} = (Q_f - e_{ch}) \times 0.9 \tag{5}$$

where $M_{N_{ch}}$ represents the unit charging price at charging station N_{ch} (unit: ¥ /kWh), v_{ij} denotes the average speed of the vehicle (unit: km/h), and P_{ch} indicates the charging power at charging station N_{ch} (unit: kW). e_{ch} indicates the remaining charge of the EV upon reaching a charging station. Q represents the total battery capacity of the EV. The economic cost of charging the EV to Q_f at charging station N_{ch} is represented by (3), while the total time consumed from the starting point n_s to the endpoint n_e of the journey is represented by (4), including the time spent charging at charging station N_{ch}. Carbon emissions are calculated by multiplying the amount of charging power required by the carbon emissions per unit by (5).

Over long-term use, EV batteries are highly prone to incidents of false battery charge indications. In actual driving conditions, external environmental factors greatly affect the battery. For example, extreme cold weather can cause rapid depletion of battery charge. Therefore, to avoid the impact of false battery charge indications on the driver's journey, if the initial charge of the EV e_{start} is less than the certain value, it is imperative to immediately find the nearest charging station to the vehicle's location and plan the shortest charging route.

$$F = \min F_{dis}^{N_{ch}} \tag{6}$$

$$e_{ch} = e_{start} - r \sum_{(i,j)\in P} x_{ij} d_{ij} \geq 0 \tag{7}$$

$$\sum_{k\in N_{ch}} y_k = 1 \tag{8}$$

$$\sum_{(i,j)\in P} x_{ij} - \sum_{(i,j)\in P} x_{ji} = \begin{cases} 1, i = n_s \\ -1, i = n_e \\ 0, otherwise \end{cases} \tag{9}$$

$$a_{i,t+1} = \left| a_{i,t} + b_{i,t} - \sum_{(i,j)\in P} x_{ij,t} \right| \tag{10}$$

$$a_{i,t} = \sum_{(i,j)\in P, \tau<t} x_{ij,t+1} \tag{11}$$

$$\sum_{i\in N} (b_{i,t+1} + \sum_{j\in N,(i,j)\in P} x_{ij,t}) \leq 1 \tag{12}$$

$$P_{\min} \leq P_{ch} \leq P_{\max} \tag{13}$$

$$x_{ij}, y_k, a_{i,t}, b_{i,t} \in \{0,1\} \tag{14}$$

where $a_{i,t}$ denotes that the EV arrives at node i or leaves node i at period t, and $b_{i,t}$ denotes that the EV stays at node i at time period t. It is assumed the EV's energy consumption rate per unit distance is r (unit: kWh/km). $r \bullet d_{ij}$ indicates the amount of electricity consumed by the EV traveling from node i to node j. e_{start} is the remaining battery charge of the EV at the starting point. n_s signifies the starting point of the EV's journey, and n_e represents the endpoint of the journey. Equation (6) indicates that when the initial charge of the EV is less than the certain value of the total battery capacity, the sole objective is to find the shortest route to a charging station. Equation (7) specifies the power consumption from the starting point to the charging station and ensures that the remaining power at the arrival of the charging station is greater than 0, which means that the EV must have enough power to reach the charging station. The charging route planning selects only one charging station as the destination is guaranteed by equation (8). Equation (9) states that the driving route of the EV is a non-repeating route from the starting point to the charging station. Equation (10) restricts the EV to only three states throughout the process: arriving at a node or leaving a node, staying at a node, or traveling between nodes. Ensuring that the EV must leave the previous node before reaching the next node is guaranteed by equation (11). Constraint (12) ensures that if the EV leaves node i and drives to node j at time t, it cannot still be at node i at time t. The charging power is limited by constraint (13). Equation (14) shows that x_{ij}, y_k, $a_{i,t}$, $b_{i,t}$ are binary variables.

When the initial charge of the EV at the starting point is more than a certain value, it becomes feasible to consider the costs at multiple stations and select the most suitable charging route. In the situation, the economic cost is required to charge the vehicle, as well as the time cost is incurred during waiting and charging.

$$F = \min(\lambda F_{pr}^{N_{ch}} + \theta F_{n_s,n_e}^{N_{ch}} + \omega F_{em}^{N_{ch}}) \tag{15}$$

$$\lambda + \theta + \omega = 1 \tag{16}$$

where λ represents the weight of the economic cost, θ represents the weight of the time cost, and ω represents the weight of the carbon emission cost.

3 Solution approach

The framework of the whole algorithm is shown on Figure 1. The degree of driver's demand for cost is described as low, medium or high demand. The fuzzy and independent user demands are transformed into accurate weight figures and assigned to the corresponding objective functions by four steps: fuzzification of inputs, application of fuzzy rules, aggregation, and defuzzification [30]. In order to improve the optimization search rate, the Depth-First Search (DFS) algorithm is utilized to find all possible charging paths. Subsequently the path with the lowest overall cost is found by EGWA.

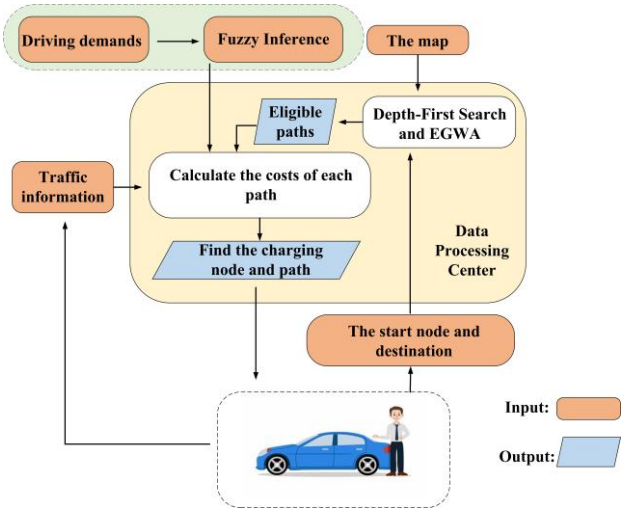


Figure 1: Outline of the proposed algorithm

3.1 Fuzzy inference

The objective function consists of economic costs, time costs, and carbon emission costs. The degree of user demand for cost is categorized as low, medium and high demand, which are represented by the numbers "0", "0.5" and "1". These numbers are used as input variables. The input fuzzy function used for fuzzy inference is the Gaussian membership function, the output fuzzy function is the trapezoidal membership function, and the inference method used is the Mamdani inference method [10].

The Gaussian functions are highly practical in models requiring differential operations, such as neural networks, clustering, and fuzzy control, and are commonly used to model user preferences [37]. The general form of the Gaussian membership function is as follows

$$\mu(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{17}$$

where x is the input variable and $\mu(x)$ is the degree of affiliation which takes values in the range [0,1]. c is the mean value, which determines the center of the curve. σ is the standard deviation, which determines the width of the curve.

The trapezoidal membership represents the membership degree of an element in a fuzzy set by a trapezoid whose top side has a value of 1 and whose two non-parallel sides increase or decrease linearly. It has a simple structure and low computational complexity, making it particularly suitable for real-time systems that require fast computation. Providing feasible charging routes for electric vehicles is such a real-time system, where it is essential to deliver solutions to users promptly. The general form is as follows

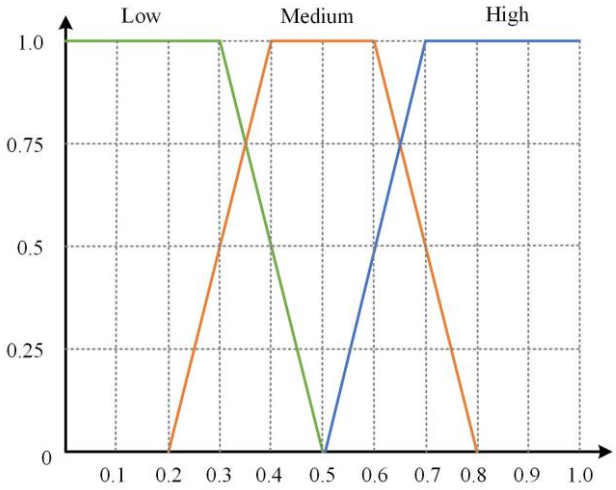


Figure 2: Output membership function

$$\mu(x) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d-x}{d-c} & c \le x \le d \\ 0 & x \ge d \end{cases} \tag{18}$$

where a and d control the left and right boundaries of the trapezoid which the part of the trapezoid with an affiliation of 0. b and c control the flat-top region of the trapezoid which the part of the trapezoid with an affiliation of 1. The implementation of weight with different types is shown in Figure 2.

The Mamdani method is commonly used to deal with systems with fuzzy rules that reason in the form of "IF-THEN" rules and deal with the relationship between inputs and outputs in the form of fuzzy sets. Each fuzzy rule is usually written as "IF ... THEN ..." which the relation-ship is $Rules=\{Rule_1, Rule_2,\ldots, Rule_n\}$.

$$\begin{cases} Rule_1 = \text{IF } x_1 \text{ is } A_1 \text{ THEN } y_1 \text{ is } B_1 \\ Rule_2 = \text{IF } x_2 \text{ is } A_2 \text{ THEN } y_2 \text{ is } B_2 \\ \ldots \\ Rule_n = \text{IF } x_n \text{ is } A_n \text{ THEN } y_n \text{ is } B_n \end{cases} \tag{19}$$

$$Rule = \text{IF } x \text{ is } A \text{ THEN } y \text{ is } B$$

A total of 27 rules is designed, with each rule mapping a specific combination of user requirements to a corresponding set of weights. During inference, relevant rules are activated, and the final weights are obtained through fuzzy aggregation and defuzzification.

The input variables are fuzzy using the Gaussian membership function and then evaluated according to the formulated rules. The fuzzy outputs of all the rules are computed based on the trapezoidal membership function to arrive at the final fuzzy set. The fuzzy outputs are transformed into exact outputs corresponding to the requirements as weights through defuzzification.

3.2 Depth-first search

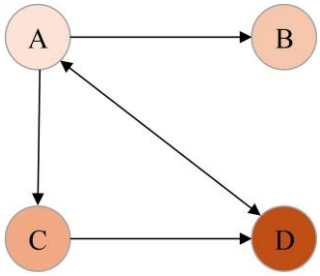


Figure 3: Principles of DFS

Traffic networks are composed of a series of nodes and the connecting lines between nodes [38]. The optimization of charging routes differs from standard route optimization problems in that the number of nodes included in each charging route can vary. Therefore, the methods for solving the charging route optimization problem need improvement.

The DFS algorithm is a graph traversal algorithm. Its basic principle is shown in Figure 3, it is visited A first and proceeded to visit the children of A, which are B, C, and D. Then if it is chosen B to visit first, B has no children. It is backtracked to A, and then visited another child node of A, C. C's children are A and D. A has already been visited, so visit D. D has no children. It is ended the traversal.

The number of nodes in the route can vary. Using binary algorithms to simply record whether a node has been visited with "0" or "1" is not feasible. The solution is to first use DFS to find all routes from the starting point to the endpoint and assign a number to each route. Then, it is randomly selected some routes and optimized them using the EGWA.

Algorithm 1 DFS

```
Initialize an empty list paths to store all found paths
Define internal recursive function dfs(currentPath):
    currentNode ← last node in currentPath
    If currentNode is in endPoints:
        Add currentPath to paths
    Return
    For each neighbor of currentNode in graph:
        If neighbor is not in currentPath:   // avoid cycles
        Call dfs(currentPath + neighbor)
Call dfs([startPoint])  // start the search from the starting point
Return paths
```

3.3 EGWA

GWO stratifies the population according to the social structure of grey wolves into four tiers, from top to bottom, α, β, δ and ω wolves. The α represents the best solution, the β represents the second-best solution, and the δ represents the third-best solution. The three wolves guide the movement of the ω wolves in encircling, harassing, and attacking the prey.

The mathematical model of the GWO is as follows. The wolves update their positions using the following position update equations and enable the population to adjust their positioning until the prey is encircled.

$$\vec{D} = \left|\vec{C} \cdot \vec{X_p(t)} - \vec{X(t)}\right| \tag{20}$$

$$\vec{X(t+1)} = \vec{X_p(t)} - \vec{A} \cdot \vec{D} \tag{21}$$

Equation (20) is used to calculate the distance between the grey wolves and the prey, while equation (21) is used to update the positions of the wolves. And the calculation formula is as follows.

$$\vec{A} = 2\vec{a} \cdot \vec{r_1} - \vec{a} \tag{22}$$

$$\vec{C} = 2\vec{r_2} \tag{23}$$

where $\vec{r_1}$ and $\vec{r_2}$ are both random vectors, with values ranging from 0 to 1. Consequently, the range of values for $\vec{A}$ is from $-\vec{a}$ to $\vec{a}$ and $\vec{C}$ can vary from 0 to 2.

To solve the complex charging route planning problem discussed in this paper, GWO is chosen in this paper because of its simplicity, ease of implementation and wide applicability. However, GWO has two drawbacks, one is the slow convergence speed at the later stage, and the other is that it is easy to fall into the local optimum. Therefore, it is used the 2-opt algorithm and the roulette wheel selection method to solve these two problems in turn.

Algorithm 2 EGWA

```
Initialize the value of α, β and δ as +∞
Initialize the position of the grey wolves
iter = 1
while iter ≤ maxiter :
 For each wolf
    update the position and numerical value of α, β and δ
 end
 Record the value of α
 For each wolf i not in {α, β, δ}:
    Select two pairs of sides to swap
      if newdistance < routedistance do
        Update Fitness and paths for wolf i
      end
end
If no improvement over several iterations:
    Update the value of α probabilistically
end
iter += 1
Return the value of α
```

3.3.1 2-opt

The 2-opt algorithm was initially proposed as an optimization method for solving the TSP. Its main goal is to find a shorter one by making improvements. It iterates through each edge in the route. It randomly swaps the positions of two points and then compares the length of the new route to the original one, as shown in Figure 4. If

the new route is shorter, it is retained. Otherwise, the path continues to be updated until no shorter path can be found or the set number of iterations is reached.

To address the slow convergence speed in the later stages of the GWO, it is integrated the 2-opt algorithm into the GWO. After a position update is completed by the GWO, the 2-opt algorithm is used to optimize the original route, reducing its length. Then, it is proceeded to the next iteration of the GWO, sought the shortest route length to assign to the α, β and δ wolves for a new round of position updates.

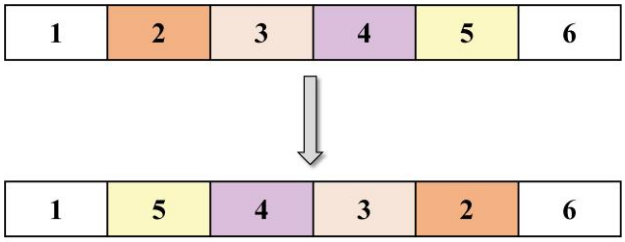


Figure 4: Principles of 2-opt

3.3.2 Roulette wheel selection

A common example of the roulette wheel selection is a spinning wheel lottery, where the area occupying the largest section of the wheel has the highest probability of being selected. It reflects the fundamental idea of the roulette wheel selection that the probability of each segment being selected is directly proportional to its relative size within the whole. Integrating the concept of roulette wheel selection into the algorithm, the relative size is replaced by the fitness value, with the calculation formula as follows:

$$p(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \tag{24}$$

$$q_i = \sum_{j=1}^{i} f(x_j) \tag{25}$$

where $f(x_i)$ represents the fitness value of an individual, and $\sum_{j=1}^{N} f(x_i)$ represents the total fitness value of the population. Equation (24) calculates the proportion of an individual's fitness value. Equation (25) calculates the cumulative probability from 1 to i. When selecting individuals, it is made choice based on the cumulative probability. It is generated a random number between 0 and 1. If q_i is greater than the random number, then corresponding individual x_i is selected.

If the best fitness value of the α wolf in GWO does not change after 10 iterations, it is determined that it has fallen into local optimality. Roulette wheel selection can be used to select one of the best fitness values of the alpha wolf in the past, assign that value to the best fitness value of the alpha, and continue to optimize until the algorithm falls into another local optimum or reaches a predetermined number of iterations. After many iterations of roulette wheel selection, if the same best fit value is determined to be a local optimum several times, it is certain that the value is a global optimum.

4 Numerical experiments

To verify the feasibility of the proposed solution, it is abstracted the traffic roads of a certain city into the traffic map as shown in Figure 5. The map contains a total of 34 nodes. Nodes 10, 16, and 31 are the locations of charging stations where EVs can complete their charging tasks. The EV starts from node 1 and has its destination at node 34. To ensure the universality of the verification, the Tesla Model Y 2023 Long Range All-Wheel Drive version is selected, which has a high sales volume [39]. The vehicle has a total battery capacity of 78.4 kWh and a power consumption of 13.4 kWh per 100 km. It is assumed the driving speed of the EV is 60 km/h, and the charging power at the charging stations is 22 kW [40].

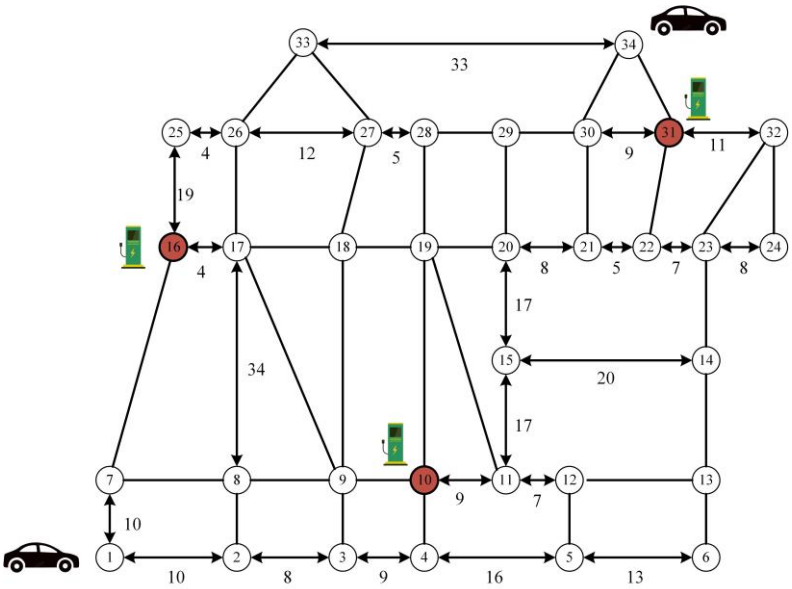


Figure 5: The map of the test section

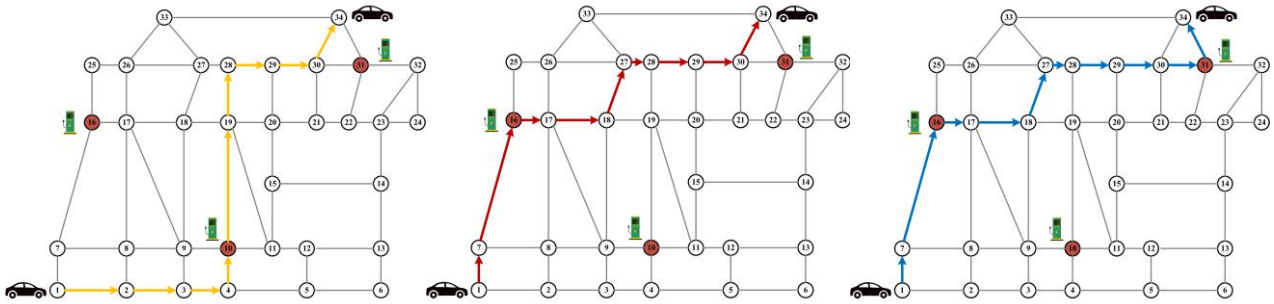
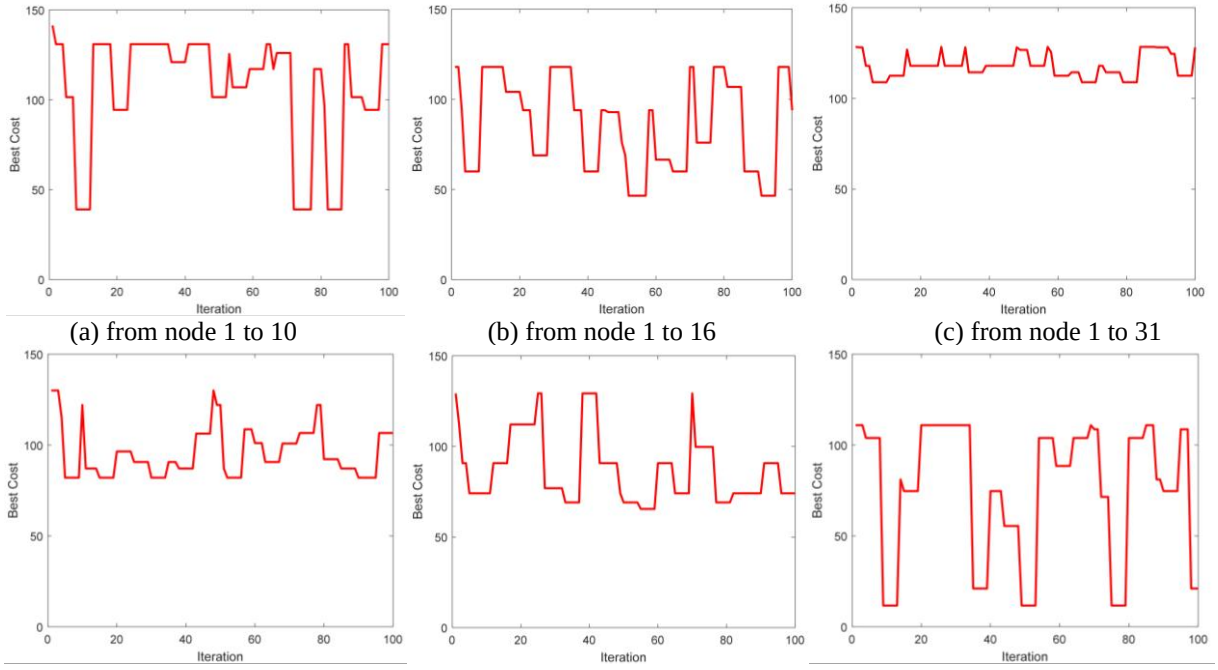


Figure 6: The shortest route from start node to destination



(a) from node 1 to 10 (b) from node 1 to 16 (c) from node 1 to 31

(d) from node 10 to 34 (e) from node 16 to 34 (f) from node 31 to 34

Figure 7: The iterative process for the shortest route

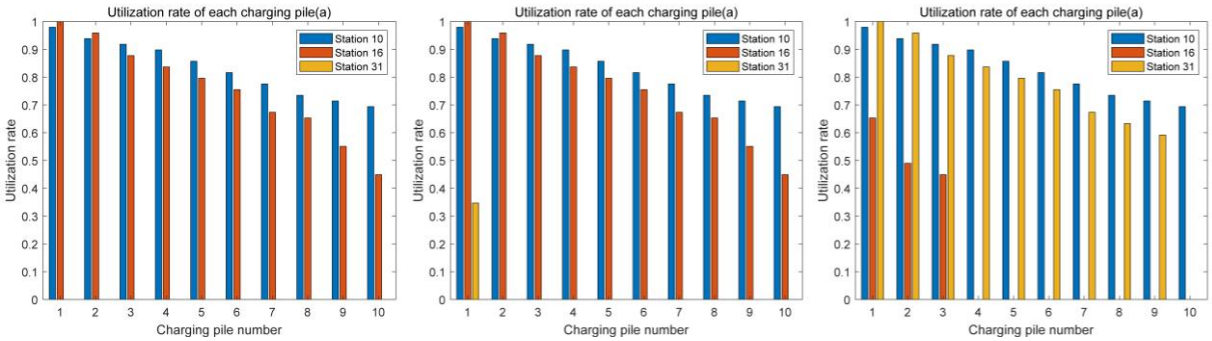
4.1 Charging route planning for a single EV

First, a specific value of 20% of the total charge is assumed. When the initial charge of the EV at the start node 1 is less than 20% of the total charge, the algorithm searches for the shortest route to a particular charging node and ensures that the EV has the charge to reach the charging station. The shortest route to each node is shown in Figure 6. The distance of the shortest route to node 10 is 39 km, the distance of the shortest route to node 16 is 46.53 km, and the distance of the shortest route to node 31 is 108.94 km. After arriving at the charging station, the electric vehicle is charged. After charging is completed, the shortest route to the destination should be planned. The shortest route lengths from the three charging nodes to the destination are as follows: the shortest route length through node 10 is 82.08 km, the shortest route length through node 16 is 65.50 km, and the shortest route length through node 31 is 11.70 km. The iterative process of the shortest path is shown in Figure 7. From the shortest path lengths obtained by EGWA, the roulette wheel algorithm can prove that the results obtained are globally optimal to a certain extent, which reduces the cases of falling into local optimization.

The route planning for a single EV is relatively simple, as it does not need to consider the waiting time at charging stations. It is assumed that the EV has 40% of its battery remaining at node 1. It is assumed the charging cost at node 10 is ¥1.3 per hour, at node 16 is ¥1 per hour, and at node 31 is ¥0.7 [41-42]. Considering the costs of each route, the driver can choose the appropriate charging station according to their needs. According to the fuzzy inference system, the user can derive an objective function that meets drivers' needs, as in equation (15). Assuming that the user attaches great importance to economic costs, input "1" to the fuzzy inference system and "0" for the rest of the costs. The system outputs the weights $\lambda = 0.72$, $\theta = 0.14$, $\omega = 0.14$. Assuming that the user attaches great importance to economic costs and time costs, input "1" to the fuzzy inference system and "0" for carbon emission cost. The system output weights $\lambda = 0.45$, $\theta = 0.45$, $\omega = 0.10$. Assuming that the user needs to balance the three costs, the system outputs $\lambda = 0.33$, $\theta = 0.33$, $\omega = 0.33$. The charging station choices for various user requirements are shown in Table 1.

Table 1: Charging options for vehicles with different needs

Inputs to the Fuzzy Inference System			Weights			Charging Station
Economic Cost	Time Cost	Emission Cost	λ	θ	ω	
1	0	0	0.72	0.14	0.14	31
0	1	0	0.14	0.72	0.14	16
0	0	1	0.14	0.14	0.72	16
1	1	0	0.45	0.45	0.1	31
0	1	1	0.1	0.45	0.45	16
1	0	1	0.45	0.1	0.45	16
1	0.5	0	0.56	0.33	0.11	31
1	1	1	0.33	0.33	0.33	16



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Figure 8: Utilization rate of charging pile under different scenarios

Table 2: Number of cars charged at each node

Scenario 1		Scenario 2		Scenario 3	
Node	Number of vehicles	Node	Number of vehicles	Node	Number of vehicles
10	24	10	24	10	24
16	26	16	25	16	10
31	0	31	1	31	16

4.3 Comparison of methods

To highlight the advantages of EGWA, EGWA is compared with other optimization algorithms in terms of minimum route length and minimum cost.

4.3.1 Minimum route length

To verify the performance of EGWA used for searching shortest paths in this paper, we have chosen GWO, LPGA [13], IWOA [42] and EGWA for comparison. The objective of optimization is to search for the shortest path from node 1 to node 10.

According to Figure 9 and Table 3, GWO finds the optimal solution 108.94 at the 47th iteration. IWOA finds the optimal solution 39 at the 64th iteration. LPGA finds the optimal solution 39 at the 84th iteration, and EGWA finds the optimal solution 39 at the 23rd iteration. EGWA keeps jumping out of the optimal solution to prove that the current optimal solution is a global optimal solution. EGWA is much better than other algorithms in terms of path finding efficiency and accuracy.

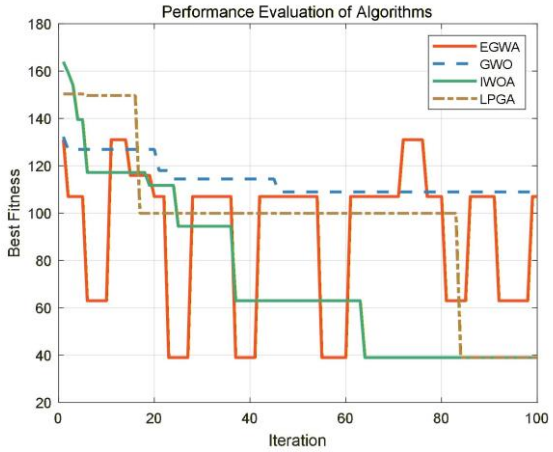
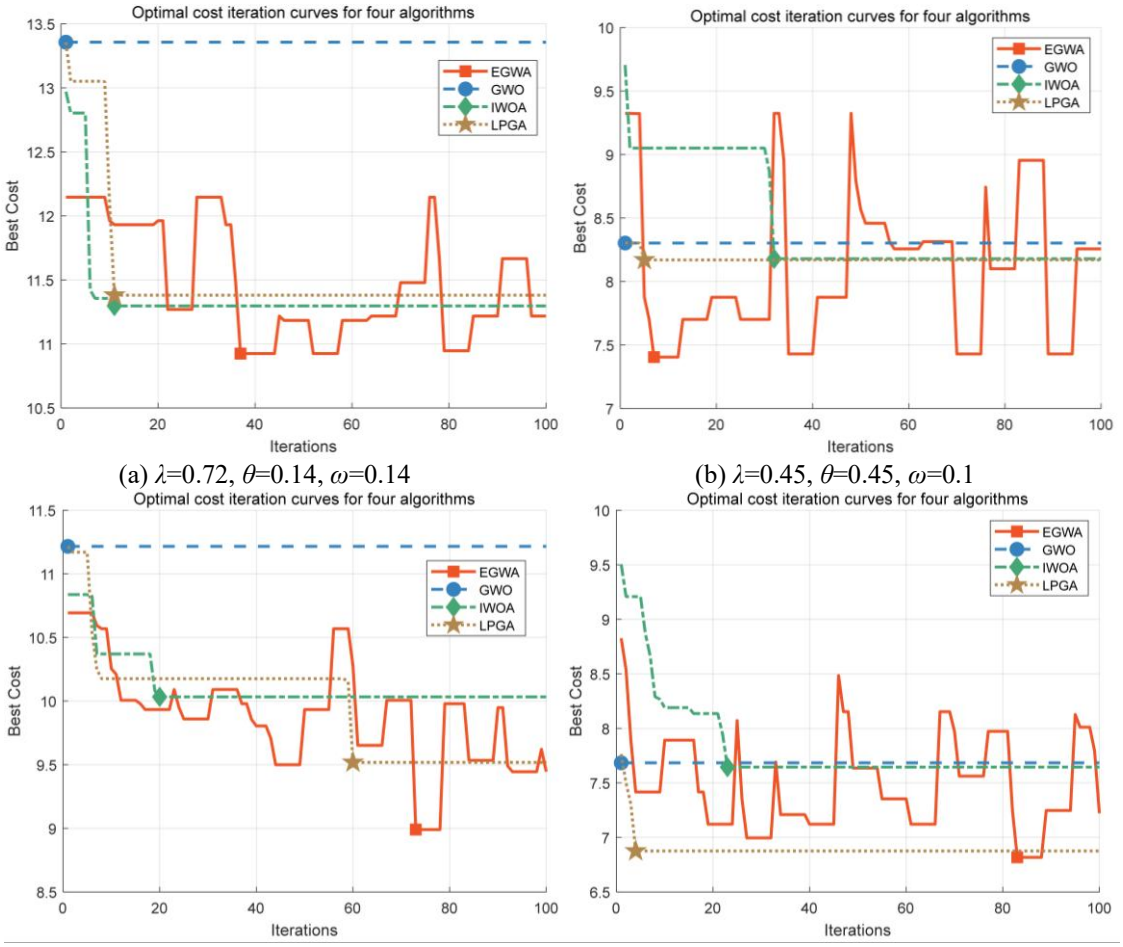


Figure 9: The comparison between EGWA, GWO, IWOA and LPGA

Table 3: Algorithm performance comparison

Algorithm	Optimal value	Number of iterations to reach the optimum
EGWA	39	23
GWO	108.94	47
IWOA	39	64
LPGA	39	84

4.3.2 Minimum cost



(a) λ=0.72, θ=0.14, ω=0.14 (b) λ=0.45, θ=0.45, ω=0.1

(c) λ=0.56, θ=0.33, ω=0.11 (d) λ=0.33, θ=0.33, ω=0.33

Figure 10: Iterative process of optimal solution with different cost weights

Table 4: Algorithm performance comparison

Weights	Algorithm	Optimal value	Number of iterations to reach the optimum	Cost savings achieved by EGWA over other algorithms
λ=0.72 θ=0.14 ω=0.14	EGWA	10.9247	37	\
	GWO	13.3566	1	22.26%
	IWOA	11.2970	11	3.41%
	LPGA	11.3809	11	4.18%
λ=0.45 θ=0.45 ω=0.1	EGWA	7.4048	7	\
	GWO	8.3028	1	12.13%
	IWOA	8.1792	32	10.46%
	LPGA	8.1700	5	10.33%
λ=0.56 θ=0.33 ω=0.11	EGWA	8.9903	73	\
	GWO	11.2161	1	24.76%
	IWOA	10.0331	20	11.60%
	LPGA	9.5184	60	5.87%
λ=0.33 θ=0.33 ω=0.33	EGWA	6.8174	83	\
	GWO	7.6840	1	12.71%
	IWOA	7.6448	23	12.14%
	LPGA	6.8755	4	0.85%

Table 5: Economic, time, and emission costs under λ=0.14, θ=0.14, ω=0.72

	Economic Cost	Cost savings achieved by EGWA	Time Cost	Cost savings achieved by EGWA	Emission Cost	Cost savings achieved by EGWA	Total Cost	Cost savings achieved by EGWA
EGWA	15.5751	\	2.1141	\	3.3994	\	4.9241	\
GWO	19.2983	23.90%	3.2130	51.98%	5.1665	51.98%	6.8715	39.55%
IWOA	15.5570	-0.11%	2.7055	27.97%	4.3505	27.98%	5.6889	15.53%
LPAG	16.2522	4.35%	2.2475	6.31%	3.6140	6.31%	5.1921	5.44%

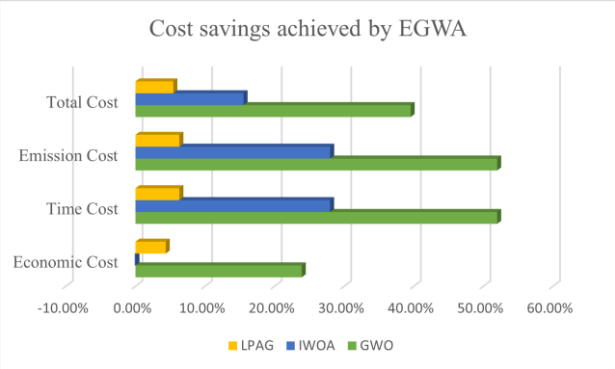


Figure 11: Cost savings achieved by EGWA over other algorithms

To highlight the superiority of EGWA in charging path cost optimization, four different cost weighting optimization iteration processes are presented.

Dealing with discrete path optimization, the position update formula of GWO is not suitable for discrete problems, and the lack of sufficient perturbation after updates leads to no population renewal, resulting in no change in the optimal value during subsequent iterations. Although IWOA and LPGA [4] can find local optima, they are prone to getting trapped in local optima, making it difficult to find the global optimum. The GWO improved by applying the 2-opt method and roulette wheel selection performs better in both population updating and optimal value searching. As shown in the Figure.10 and Table. 4, EGWA consistently achieves the lowest cost under different weight settings. On average, EGWA saves 12.47% more cost than GWO, 9.27% more than IWOA, and 5.08% more than LPGA.

According to the Figure. 11 and Table. 5, the use of EGWA results in an average reduction of 28.76% in carbon emission costs. A comparison between EGWA and IWOA shows that although EGWA does not achieve the lowest value for every individual cost component, its disadvantage in economic cost, whose weight is relatively small in the total objective function, is offset by its advantage in carbon emission cost, which has a higher weight. As a result, EGWA achieves a 15.53% reduction in the overall cost. This demonstrates that even if EGWA does not find the optimal solution for all sub-objectives, the overall cost is primarily determined by the sub-objectives with larger weightings. Therefore, achieving better performance in the dominant sub-objectives can still significantly reduce the overall cost.

5 Conclusion

This paper focuses on the charging route optimization problem under the scenario of multiple charging stations with different charging tariffs and different objective functions. A fuzzy inference system is used to allocate weights to the objective function, providing greater flexibility and comprehensiveness. By applying Depth-First Search (DFS) and an Improved Grey Wolf Optimizer (EGWA), suitable charging routes can be selected to improve the accuracy and efficiency of route optimization. Simulation of an EV fleet shows that node charging prices and waiting times have significant impacts on drivers' route choices. Simulation of a single EV demonstrates that EGWA has an irreplaceable advantage in minimizing charging costs. However, in real-world studies, battery degradation of EVs is inevitable, and aging may lead to inaccurate estimation of available energy and charging demand. In addition, carbon emission factors and charging prices may fluctuate with grid load, time, and regional policies. Traffic flow in route planning is also critical, as its dynamic changes can significantly affect waiting times. Therefore, future work will couple traffic flow and road network relationships, take into account the impact of battery aging on available energy, and establish a system model that is closer to real-world conditions. This will improve the realism and robustness of the optimization model and further refine the algorithm to achieve better results in EV charging route planning.

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A Hybrid MIP-DES Framework for Open-Pit Mine Planning Using OPPS: Optimization and Simulation-Based Decision Support

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Optimizing mine planning maximizes economic value and efficiency by designing pit limits, scheduling extraction, allocating equipment, and managing costs. Traditional methods often fail to handle randomness and dynamic field conditions. To overcome these limitations, this research introduces a simulation-optimization framework integrating Mixed-Integer Programming (MIP) for pit limit design with discrete-event simulation (DES) to capture short-term operational variability. MIP indicates greater flexibility in incorporating complex constraints, resulting in a more realistic pit design. The geometry of open-pit layout growth is modeled using an Open Pit Production Simulator (OPPS), implemented in MATLAB and based on a modified elliptical frustum. The OPPS serves as a central tool, seamlessly linking the MIP-derived scheduling outputs with DES-based operational scenarios for realistic system evaluation. The simulator models equipment movements, haulage cycles, and scheduling under uncertain operational conditions. The framework dynamically interacts with a geological-economic block model to compute volumes of ore, waste, and stockpiles, while continuously tracking the Net Present Value (NPV). A case study on a 75,000-block iron ore deposit validates the framework. For 1,000 discrete-event simulation scenarios, the MIP-optimized pit design forms the foundation. At an annual discount rate of 8%, the best-performing scenario (OPPS) achieved an NPV deviation of -1.5%, maintained average ore grades of ~67%, and stripping ratios between 5.2–6.5, with a balanced annual production schedule of ~12 Mt ore and ~7 Mt waste over a 30-year my life. Overall, the proposed MIP-DES framework improves mine planning by combining optimization and simulation, enabling informed, long-term, and realistic operational decisions under uncertainty.

Povzetek: Hibridni okvir združuje mešano celoštevilsko programiranje in diskretno-dogodkovno simulacijo za planiranje površinskih kopov. Pristop omogoča realističnejše odločanje pod negotovostjo ter izboljša NPV, razmerje jalovina–ruda, stabilnost kakovosti in izrabo opreme.

1 Introduction

The extraction of mineral resources is a key pillar of industrial development, and open-pit mining is the most common method to extract ore bodies located near the surface. Open-pit mining is economical due to the ability to sustain large, continuous production, making it advantageous for bulk commodities such as iron ore, copper, and gold [1]. During the last ten years, the mine planning landscape has seen significant changes as a result of increasing geological complexity, varying commodity prices, new environmental legislation, and the complexities of managing extremely large open-pit systems [2]. The decisions of long-term planners, such as the order of block extraction or fleet allocations, tend to have more deliberate outcomes with potentially distinct impacts that often affect the mine's Net Present Value (NPV) across decades. This allows sophisticated tools capable of representing variability, assessing risk, and modifying plans as it unfolds [3]. In open-pit situations, this difficulty is multiplied as the interactions among variables relate to the system over time, while uncertainty is extremely low [4]. Computer-based simulation provides a new way to deal with this complexity and uncertainty. Simulation models replicate the time-dependent behavior of mine systems so that planners can test alternative strategies for the sequence of extraction and allocation of equipment and uncertainties, all at no risk of going on the mine [5]. Combining simulation and mathematical optimization provides an additional pathway to develop their value. While optimization can provide schedules or designs to optimize economic performance, simulation can

also verify that the step is still valid successfully as operational uncertainty [6]. As the industry moves forward in hyper-automation, efficiencies, and resiliencies, as a standard for open-pit operations, it is not a choice but a necessity to deliver competitive and sustainable mineral resource use [7].

Research aim: This research intends to construct an intelligent simulation-optimization model (OPPS) for open-pit mine planning that integrates MIP and DES. It aims to evaluate whether this hybrid approach can improve key performance metrics, such as reducing stripping ratio or waste-to-ore ratio, ore grade stability, maximizing equipment utilization, and minimizing NPV deviation under uncertain cycle times, compared to conventional planning methods, and to determine its robustness under operational uncertainties.

The organization of the research is listed as follows: Section 1 discusses the significant background of research; Section 2 offers the prior studies in mining planning of mines using computer simulation technology. Section 3 provides the proposed methodology, Section 4 illustrates the experimental findings, and Section 5 deals with the conclusion and future direction of the research.

2 Related works

Table 1 contains a comparative overview of related works undertaken between 2022 and 2025 relating to Machine Learning (ML) methods, DES, and optimization methods in open-pit mining.

Table 1: Summary of related works

Ref	Objective	Data Used	Key Result	Limitations
Park et al. [8]	Predict ore production using ML with DES in haulage systems	Limestone underground mine truck data	Particle Swarm Optimization – Support Vector Machine (PSO-SVM) accurately predicted cycle time & ore production.	Focused only on underground limestone mines; not tested on open-pit mines
Qiao et al. [9]	Extract open-pit mining areas from multispectral images using deep learning.	Multispectral satellite imagery	SegMine (Transformer model) outperformed 6 variants in mIoU, precision, and recall.	Geared toward image extraction, not direct mine planning
Quelopana et al. [10]	Technoeconomic assessment of intelligent ore sorting for open-pit mines using an integrated MIP-DES framework	Gold deposit data, operational mine & plant constraints	Proposed integrated methodology optimizes pit design and operational scheduling, handling geological uncertainty and feed variability, improving NPV	Limited to a simulated case study; requires real-time implementation validation
Fan et al. [11]	Forecast ore production using a Deep Neural Network combined with Principal Component Analysis (DNN + PCA) in open-pit mines	Truck haulage and weather data	Deep Neural Network (DNN) achieved high forecasting accuracy for ore tonnage.	Limited focus on prediction; doesn't support operational simulation
Gong et al. [12]	Develop and evaluate the Near-Face Stockpile (NFS) method, integrating IPCC with the pre-crusher stockpile for large open pits.	Oil sands mine case study + MILP optimization + DES simulation	NFS improved production by 5.06%, reduced truck haulage distance by 17.87%, and increased shovel and crusher utilization by ~5%	Requires a wider pit bottom layout; applicability to narrow pits is limited
Quelopana et al. [13]	Assess tech upgrades in open-pit mines using optimization + DES	Mine plan data + processing constraints	Integrated system maximizes throughput despite feed uncertainty	Doesn't address block-level scheduling or grade optimization
Eustace and Hynard [14]	Support rapid weekly/daily mine plan refinement using simulation and optimization to align execution with actual my operations.	Operations data feed from active mines (actual vs. planned state)	Optimization + simulation enabled automated generation of short-term plans that maintained or improved performance objectives of quarterly plans; tested robustness and operational issue mitigation	Example applications discussed; generalizability to all mine types not fully validated; requires integration with live operations data
Xu et al. [15]	Optimize production + haulage planning via bilevel optimization	Open-pit mine block + route data	Joint model reduces costs and adjusts demand temporally	Computational complexity increases with mine size
Icarte-Ahumada and Herzog [16]	Improve truck dispatching with reinforcement learning in open-pit mines	Truck routing + dispatch logs	Learning-based Multi-Agent System for Truck Dispatching (MAS-TD) outperformed the original dispatch system.	Focuses only on dispatch logic, not on full mine scheduling

Li et al. [17]	Forecast mining capital cost (MCC) for open-pit projects	80 open-pit mining projects	SalpSO-CFNN model achieved high accuracy ($R^2 = 0.98$)	Limited dataset, may need more diverse mines
Zheng et al. [18]	Predict coal roadway roof displacement for safety	Dataset of six influencing factors	Random Forest model predicted roof displacement accurately ($R^2 = 0.92$)	Limited to specific coal roadway data

The mining industry faces ongoing challenges in accurately predicting production, optimizing haulage, and coordinating planning under uncertain operational conditions. Traditional machine learning and heuristic approaches often address individual tasks but fail to provide a unified framework for scheduling and simulation. The research [13] examined technology enhancement in open-pit environments and achieved robust throughput under uncertainty by combining mine plan optimization with discrete-event simulation. While the reinforcement learning-based truck dispatching system [16] enhanced dispatch logic, it was unable to optimize total production planning since it just addressed truck routing and did not incorporate comprehensive mine scheduling. The lack of integration of block-level scheduling, uncertainty modeling (ore grade, equipment delays, and market fluctuations), and optimization complexity management in these SOTA approaches further restricts their practicality. To address these limitations, this research implements the Open Pit Production Simulator (OPPS) integrated with Mixed-Integer Programming (MIP) and Discrete-Event Simulation (DES). The OPPS uniquely overcomes the shortcomings of prior methods by incorporating block-level scheduling, uncertainty modeling, and system-wide optimization, thereby ensuring higher planning accuracy and improved economic stability. This hybrid MIP-DES approach enables comprehensive mine planning, capturing both long-term pit design and short-term operational variability, thereby improving production stability, equipment utilization, and economic outcomes.

3 Proposed methodology

Rooted in data-driven mine planning, this methodology integrates the MIP and DES in an effective linear program framework. Figure 1 depicts the flow of the methodology section.

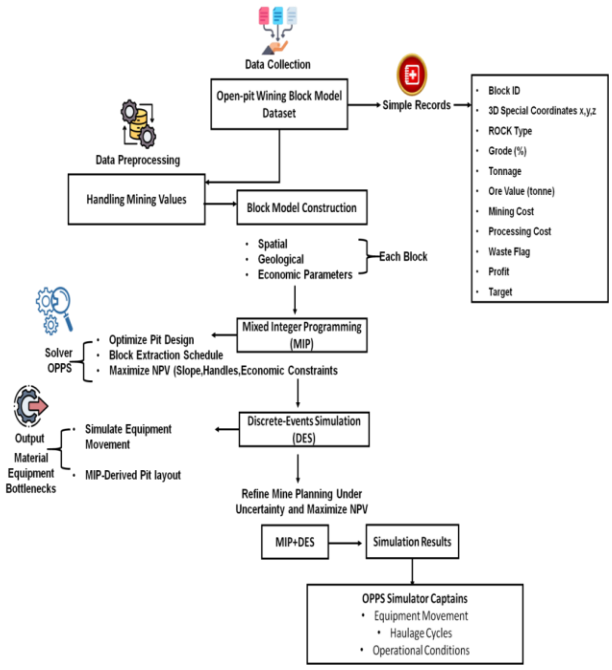


Figure 1: Methodology flow

3.1 Data collection

The open-source dataset (https://www.kaggle.com/datasets/ziya07/open-pit-mining-block-model-dataset/data) used in this research consists of a generated open-pit mining block model of 75,000 blocks. Each block contains a finite quantity of earth material that can be mined. The block model portrays realistic geological, economic, and spatial characteristics indicative of large-scale mineral production operations. Individual blocks are characterized by 3D spatial coordinates (X, Y, Z), rock type (i.e., Hematite, Magnetite, Waste), ore grade (% Fe), tonnage, ore value, operating and processing costs, and profit information. All blocks have a binary target label identifying whether or not it is economically extractable.

3.2 Data preprocessing using missing values handling

Missing values are a common problem in mining datasets due to inconsistencies in geological surveys, data entry errors, or incomplete estimation of ore properties. When it comes to open-pit mine planning, it is essential to account for missing values, as they can affect block classification, economic viability, and ultimately the accuracy of optimization. If missing values are not treated appropriately, this may lead to faulty pit designs, misclassification of ore excess, and inaccurate scheduling conditions. The missing records are considered part of the preprocessing pipeline. For continuous attributes such as ore grade, tonnage, or net present economic value, the missing entries are estimated through imputation techniques, such as mean imputation or spatial averaging of adjacent blocks. For categorical fields (e.g., rock type, waste flag, etc.), mode imputation or rule replacement was used. Blocks with critical values missing in multiple fields or undefined spatial coordinates were also excluded from the modeling process to maintain integrity. By appropriate imputation and respect for the geological structure and economic coherence of the block model, the dataset can be relied upon for simulation and optimization. The OPPS can run without encountering any computation interruptions or bias that may result from incomplete input data.

3.3 Block model construction

A 3D block model is created of the entire ore body and surrounding waste material, with each 3D block having defined spatial coordinates (X, Y, Z) inside the model plus associated geological properties defining rock type and ore grade, and economic properties including mining cost, processing cost, and expected revenue. This structure allows for profitability and feasibility calculations on a block-wise basis, providing a basis for pit design, production scheduling, and economic optimization. Importantly, the cubical block model integrates spatial and economic data to provide ongoing effective planning and decision-making throughout the life of the mine.

3.4 Mixed-integer programming (MIP) for pit design and scheduling

The MIP model calculates the optimal order of extraction for blocks in an open pit over multiple years. The model includes economic values with pit slope constraints and operational parameters to maximize NPV. After the optimized pit shell and schedule are determined, the results are input to the DES model of a real-world mining process, including haulage delays, equipment use, and stockpiling. The MIP model is constructed using a mathematical modeling language such as the open-source solver (OPPS). The decision variables are binary for when to extract a block, and continuous variables for costs and revenues. The solution to the MIP model provides the optimal sequence of block extraction, which can be input into the discrete-event simulation module. This process allows the long-term pit design to conform to technical constraints and financial goals. Using simulation results, operational costs were estimated for each block using MIP. The MIP appeared to be designed in a mathematical programming language and completed through OPPS (optimization software). To optimally plan production, operational costs were removed from revenue to create undiscounted revenue streams for each block's extraction stage. NPVs are determined based on operational results for each haulage option. Open-Pit Mining determined the undiscounted revenues for each block's extraction stage, and this became the basis for optimizing production planning. The goal was to optimize the NPV of every operation through establishing the ideal production plan for every stop (Equation 1).

$$Max: \sum_{t,s} m_s \times de_t \times x_{ts} \tag{1}$$

Where$\sum$ the summation is over **all blocks** t and **all time periods** s. m_s is the amount of the discount rate for a time frame, de_t is the undiscounted cash flow for every block, and x_{ts} denotes the binary parameter necessary for reflecting block operational circumstances. The MIP concept also includes different constraints (shown as Equations 2 to 6) that represent the actual boundaries required upon the sublevel stopping mechanism across the long-term planning perspective. These limitations can be classified based on the restrictions they place on supplies, sequencing, and scheduling.

$$\sum_{t\in\beta_s} q_s \times x_{ts} \le td_s \forall s \tag{2}$$

$$\sum_{t\in\beta_s} x_{ts} \ge x_{t's} \forall\, s, |t' \tag{3}$$

$$\in\ mbm_t$$
$$x_{ts} + x_{t's}$$

$$\forall\, t, s \mid t' \in\ mbm_t \tag{4}$$
$$\sum_{t\in\beta_s}^{\le 1} x_{ts} \le 1\ \forall t\ |k_t > S$$

$$\sum_{t\in\beta_s} x_{ts} = 1\ \forall t\ |k_t \le S \tag{5}$$

$$\tag{6}$$

In the above equations, $t \in \beta_s$ represents the truck/shaft/conveyor fleets' moving capability for every single interval s, β_s is the set of blocks considered in the period. q_s is the extraction reserves (s) for every block, td_s is the available hauling. t' is another block that must follow the precedence rules. mbm_t is the set of blocks that are mutually exclusive or have a mining dependency with

block and k_t is the block's most recent starting time. $\forall s$ for all time periods and $\forall t$ for all blocks. Constraint (2) prevents the supply of all advancement and block extracting ore from surpassing the truck/shaft/conveyor equipment capacity in any long-term duration. All subsequent operation sequencing among stops is also governed by restrictions (3) and (4). Constraint (5) assures that block output is started only once within an extended planning horizon if the scheduled opening date falls outside of the planning horizon. Block development must commence at a certain point in the long-term planning horizon if the late start time is within that time frame due to Constraint (6). Each of these modeled equations was utilized in the construction of the optimal production scheduling and mining plan corresponding to each haulage type, which considered commodity price volatility, mining rates, fixed costs, operating costs, and differences in ore quality. By restricting block extraction to practical operational, slope, and sequencing circumstances, these limitations together define the viable solution space. While Constraints (3) and (4) impose precedence and dependence restrictions that limit the flexibility of the solution, Constraint (2) ensures that haulage capacity is never exceeded, hence narrowing feasibility. Block start timings are controlled by constraints (5) and (6), which further refine workable schedules. These restrictions decrease unrealistic solutions by restricting the viable region, but they may also raise the computational load, which might have an impact on solver convergence. This trade-off between computational efficiency and solution feasibility results in the observed optimality gap of 1-2 %.

Figure 2 represents the planimetric layout of an open-pit mine, divided into four directional quadrants: Northwest (NW), Northeast (NE), Southwest (SW), and Southeast (SE). The layout illustrates the key dimensional parameters:

a_w: Horizontal distance from the center to the western edge of the pit.

a_e: Horizontal distance to the eastern edge

b_N: vertical distance from the center to the northern edge

b_s: Vertical distance to the southern edge

The arrow indicates measurement directions, and the N arrow provides orientation with true north.

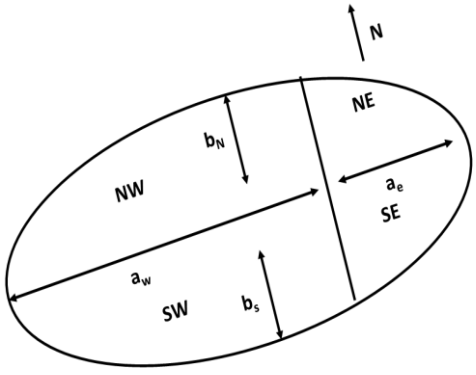


Figure 2: Planimetric layout of an open-pit mine

The MIP solver configuration for the open-pit mine planning model is summed up in Table 2. Convergence behavior, runtime, and iteration limitations, decision variables, solver type, and imposed restrictions are all included. By taking into consideration actual operational constraints, these parameters guarantee that the optimization produces workable, nearly ideal solutions.

Table 2: MIP solver settings for open-pit mine planning

Parameter	**Value / Description**
Solver Type	MILP solver in OPPS
Mathematical Model	Mixed-Integer Programming
Decision Variables	Binary (block extraction) and continuous
Runtime Limit	8 hours per scenario
Convergence Behavior	>90% scenarios converged to near-optimal; remaining within 1–2% of best-known objective
Iteration Limit	Default OPPS settings
Optimality Gap	1–2%
Constraints	Pit slope, haulage/equipment capacity, extraction sequencing, scheduling regulations
Hardware Used	MATLAB 2021b, 8 GB RAM, 2.4 GHz processor

3.5 Discrete event simulation (DES) for operational dynamics

A Discrete-Event Simulation (DES) model is employed to capture the short-term variability and intricate real-world dynamics of mining operations. Discrete-event simulation permits the time-based events in the system, including truck loading, hauling delays, queuing, equipment downtimes, and production rate realities. Events in the simulation occur at discrete time events, permitting a detailed, realistic evaluation of mine system performance. Geological uncertainty is also accounted for with the use of probabilistic distributions for ore grade, cycle times, and equipment availability. This dynamic simulation enables "what-if" analysis and supports decision-making on the strength of the MIP-optimized schedule and the variability of operations. In addition to those what-if answers, the output of the DES also includes metrics on performance, including material movement, equipment usage, delays in scheduling, and an NPV effective display. DES approaches simulate the relationships of important process parameters and their settings in response to a series of discrete events

across the year. The system's adoption of different modes of operation and management mechanisms, including stockpiling, enables it to accommodate variation in inputs and departures from anticipated ore ratios. The trade-offs of operational strategies were assessed, and the thresholds for the implementation of those strategies were determined. The modeling of extended operational periods enables the detection of possible faults or bottlenecks in integrating unit operations within the intended network.

The structure created for the research obtained ore blocks derived from the long-term planning optimization MIP, as well as the previously established variables, including functioning styles, metallurgical wellness, metal cost, maximum processing capability, and related cost. Additional control settings include manufacturing campaigns and maintenance durations, stockpile stages, and essential ore concentrations. The DES concept tries to optimize ore processing productivity, which impacts the project's overall net present value. The result is an improved risk assessment with total NPV. For efficient open-pit mine planning, this research integrates MIP for long-term block scheduling with DES to capture operational realities over short time scales. The MIP model maximizes NPV, subject to economic constraints, slope stability, haulage capacity, and precedence rules, to conclude the optimal sequence of extraction of blocks. Binary decision variables indicate the extraction state of each block at each time step, while revenues and costs are continuous variables. Through scenario-based NPV analysis, stochastic modeling of equipment cycles, and probabilistic distributions, the system also manages ore grade, equipment delays, and price changes, allowing for sound decision-making in the face of real-world uncertainty.

The DES was implemented in MATLAB 2021b (8 GB RAM, 2.4 GHz) using a custom event-driven simulation engine, with parameters summarized in Table 3. Equipment attributes, operating conditions, haulage and processing variations, ore grade distributions, stockpile restrictions, and economic considerations are all included. Together with the MIP-optimized schedule, these factors guarantee that the simulation accurately depicts short-term unpredictability, operational restrictions, and financial performance, facilitating trustworthy decision-making. According to the model, equipment failures are random occurrences with a uniform probability that corresponds to 2% to 5% of operating hours. In order to capture stochastic operational disruptions, the event-driven simulation incorporates the downtime that each failure causes for the impacted equipment.

Table 3: Key discrete-event simulation (DES) parameters for open-pit mine planning

Parameter	Description / Value
Number of trucks	10–20
Loader capacity	5–10 tonnes per cycle
Haulage cycle time	18–25 min (with variability)
Equipment downtime	2–5% of operational hours
Stockpile limit	15,000–20,000 tonnes
Ore grade distribution	60–70% Fe
Extraction sequence	From the MIP model
Simulation horizon	30 years, daily events
Economic factors	Costs, revenues, and NPV with 8% discount rate

The hybrid modeling approach allows scenarios to be created to expose bottlenecks in the system or delays in processing status, assess the toughness of the system, and improve planning in periods of operating uncertainty. In conclusion, integrating the MIP and DES processes enables better prediction of profitability and adds realism and reliability to planning an open-pit mine. Algorithm 1 illustrates the MIP-DES method, which uses MIP to schedule block extraction, DES to simulate short-term operations, MIP to handle equipment restrictions, and NPV and ore production to facilitate decision-making.

Algorithm 1: MIP-DES framework

```
# Step 1: Initialize mine data and parameters
blocks = load_mine_blocks()        # Load all mining blocks
time_periods = range(1, N + 1)     # Planning horizon
resources = initialize_equipment() # Trucks, loaders, etc.
MIP_schedule
= {}                 # Dictionary to store MIP block schedule
DES_results = {}                   # Dictionary to store DES results
# Step 2: Solve MIP for long − term optimal pit schedule
for block in blocks:
  For t in time_periods:
    # Check feasibility constraints for block extraction
    if slope_ok(block) and capacity_ok(block, resources):
      MIP_schedule[block] = t  # Schedule block extraction
      break              # Stop after assigning earliest feasible period
    else:
      MIP_schedule[block] = None
# Step 3: Run DES for short − term operational simulation
for t in time_periods:
  for block, scheduled_time in MIP_schedule.items():
    if scheduled_time == t:
      # Check if equipment is available
      if equipment_available(resources):
        extracted, ore_grade = extract_block(block, resources)
        DES_results[block] = {
          'time': t,
          'extracted': extracted,
          'grade': ore_grade
        }
      else:
        # Equipment unavailable, delay extraction
        DES_results[block] = {
          'time': t,
          'extracted': 0,
```

```
        'grade': None
    }
# Step 4: Compute performance metrics
total_NPV = 0
total_ore = 0
for block, result in DES_results.items():
  if result['extracted'] > 0:
    total_NPV +
= compute_NPV(result['extracted'], result['grade'])
    total_ore += result['extracted']
# Step 5: Output results
print("Total NPV:", total_NPV)
print("Total Ore Extracted:", total_ore)
print("Block − wise DES Results:", DES_results)
```

4 Result

The computational run time on a MATLAB 2021b system with 8 GB RAM and 2.40 GHz processor was ~6 hours for 1,000 scenarios. Compared with heuristic tools like Whittle, OPPS achieved more stable stripping ratios, ore grades, and NPV values, highlighting a trade-off between computation times and planning accuracy.

Computational metrics of the MIP-DES mine planning

The MIP-DES mine planning framework's primary performance metrics are compiled in the Table 4. Practical viability is demonstrated by the computational runtime (~6 hours per 1,000 cases). Sustainability is reflected in energy use (12–15 kWh/ton) and environmental effect (5–7 kg CO_2/ton). The convergence/optimality gap (1–2%) shows that solutions are close to optimal, whereas equipment utilization (80–90%) shows effective resource use. When combined, these measures evaluate the suggested mine planning model's dependability, operational effectiveness, and environmental responsibility.

Table 4: Performance, Sustainability, and Computational Metrics of the MIP-DES Mine Planning Framework

Parameter	Description / Value
Computational runtime	~6 hours per 1,000 scenarios
Energy consumption	12 – 15 kWh/ton (approx.)
Environmental impact	5 – 7 kg CO_2/ton
Equipment utilization	80 – 90%
Convergence/optimality gap	1–2%

The statistical validation of the MIP-DES simulation results based on 1,000 scenarios is shown in Table 4. Average performance parameters, such as equipment utilization, NPV deviation, ore grade, and stripping ratio, are indicated by the mean values. Assuring the robustness and dependability of the suggested mining planning framework, standard deviations (σ) illustrate the variability among scenarios, while 95% confidence intervals indicate the range within which the real mean is anticipated to reside.

Table 4: Statistical Validation of MIP-DES simulation results

Metric	Mean Value	Standard Deviation (σ)	95% Confidence Interval
Stripping Ratio	5.85	0.35	5.78 – 5.92
Ore Grade (%)	67	2.1	66.6 – 67.4
NPV Deviation (%)	-1.5	0.6	-1.62 – -1.38
Equipment Utilization (%)	85	4	84 – 86

The OPPS framework efficiently handled the 75,000-block dataset used in this study. Sensitivity tests indicate that it maintains stable NPV, stripping ratios, and equipment utilization under variations in ore grade and operational parameters, demonstrating robustness.

4.1 Dimensions of the open pit

Figure 3 illustrates the temporal evolution of key geometric parameters of the open-pit mine over a 30-year horizon. The dimensions include: **aW** increases steadily from ~830 m to ~1100 m, while **aE** expands linearly from ~100 m to over 500 m. **bN** and **bS** both rise from ~200 m and ~30 m, respectively, to ~260 m and ~55 m. **h**, The depth of the pit, grows consistently from ~85 m to ~200 m by year 30. This growth indicates a controlled and continuous expansion of the pit geometry, directly aligning with block extraction and scheduling decisions. These trends reflect the model's ability to simulate realistic pit evolution over time, accounting for both spatial constraints and economic viability.

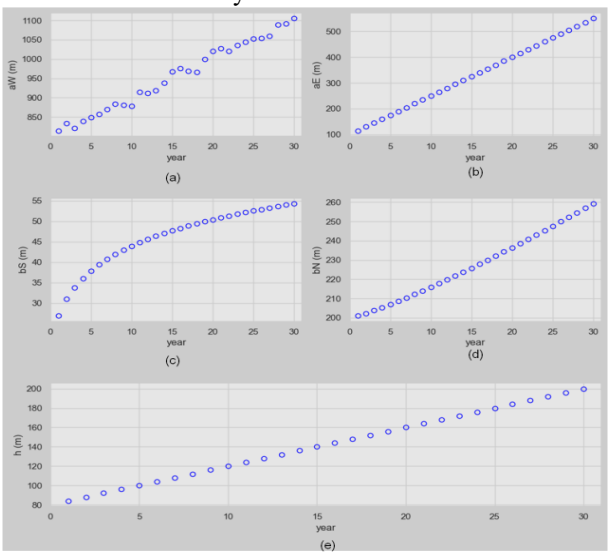


Figure 3: Yearly modification in open-pit the dimensions

4.2 Expansion of the open-pit mine

Figure 4 illustrates the progressive expansion of the open-pit mine layout between years 24 and 26, referred to as "pushbacks." Each colored layer represents a different depth and lateral extent of material removal for that period, with colored points corresponding to individual blocks planned for extraction. Numerically, the vertical axis (Elevation) shows increasing pit depth over time, while the horizontal axes (Easting and Northing) demonstrate spatial growth. The dense clustering and tiered shape imply systematic bench development concerning slope and safety constraints. Additionally, cumulative NPV and extracted tonnage overlays have been added to each pushback layer, showing the economic and production impact alongside spatial expansion. This demonstrates how the MIP-DES framework effectively integrates long-term pit planning with short-term operational outcomes. In this research, the figure highlights how the MIP-generated schedule integrates with the DES-driven operational simulation to accurately model real-world pit expansion. It confirms the effectiveness of the hybrid framework in tracking ore-waste sequencing while maintaining pit stability and spatial consistency across multi-year schedules.

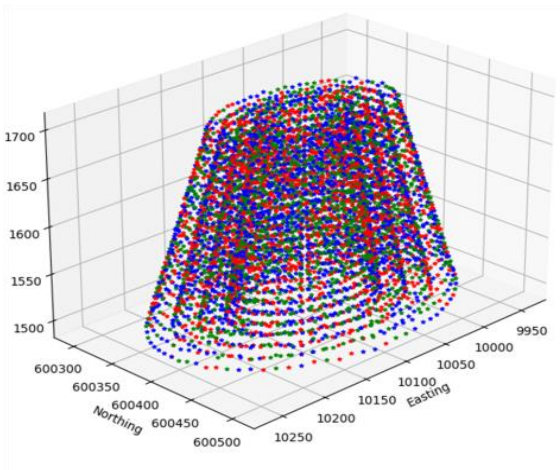


Figure 4: Simulated pushback progression using hybrid MIP-DES framework

4.3 Stripping ratio

Stripping ratio (SR) is the ratio of waste material removal to ore material extracted. SR is a crucial metric for mine planning because SR affects overall cost and economics. As shown in Figure 5, OPPS consistently maintains a low and stable SR between 5.2 and 6.5, highlighting its superior efficiency in managing waste-to-ore extraction. In contrast, Gurobi shows moderate variability with a sharp spike to 10 at year 15, while Whittle exhibits erratic behavior, peaking at 14, 18, and 16 in years 5, 12, and 20, respectively. The consistent performance by OPPS demonstrates its robust and cost-effective approach for long-term open-pit my planning. The lower and stable SR values reflect OPPS's capability to minimize waste removal, making it more suitable for sustainable and economically optimized mining operations.

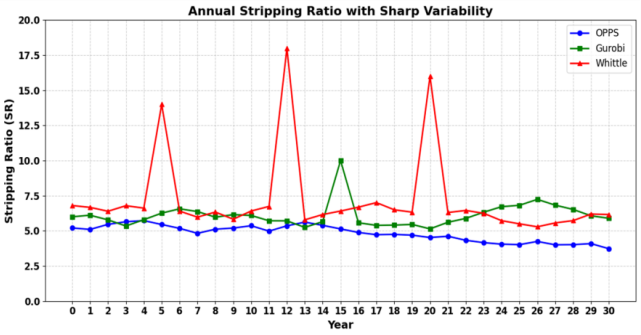


Figure 5: Annual stripping ratio with sharp variability

4.4 Average grade (%) of iron ore content

Average grade (%) indicates the iron content within the ore blocks mined annually, directly influencing the economic value of extracted material. Higher grades lead to better revenue per processed tonne. In Figure 6, OPPS maintains the highest and most stable grade, around 67%, Gurobi fluctuates near 64.5%, and Whittle trails with more volatile values, averaging ~62%. No values fall below 60% across the methods. The consistently higher ore grade in OPPS scheduling suggests better block selection aligned with profit optimization. This supports the strength of OPPS in maximizing ore quality, enhancing processing efficiency, and NPV.

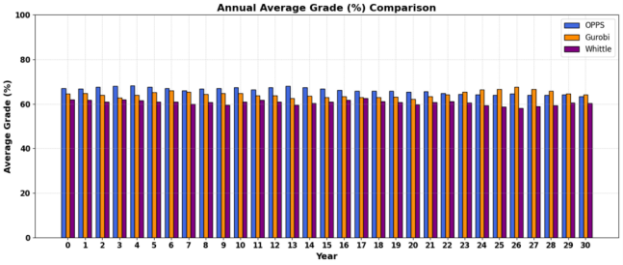


Figure 6: Annual average grade (%) comparison

4.5 Haulage cycle time

Haulage cycle time refers to the average time taken by mining trucks to complete a full load-haul-dump-return cycle. It directly impacts productivity, fuel usage, and scheduling efficiency in my operations. In Figure 7, OPPS shows the lowest cycle time, ranging around 18–19 mins, Gurobi remains moderate between 20–21.5 mins, and Whittle records the highest times, peaking near 24–25 mins across the years. The shorter haulage times under OPPS reflect better scheduling and reduced equipment idle time. This implies that OPPS ensures faster material movement, improving operational throughput and lowering logistical costs.

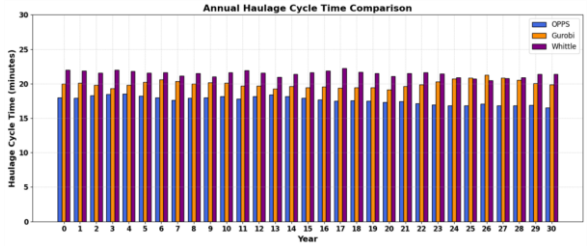


Figure 7: Annual haulage cycle time comparison

4.6 Equipment utilization rate

Equipment utilization rate measures how effectively mining machinery is used over time, expressed as a percentage of operational time versus available time. High utilization indicates efficient deployment and minimal downtime. In Figure 8, OPPS maintains a high utilization rate of around 89-91%, Gurobi ranges around 84-87%, while Whittle lags with more variation, fluctuating between 78-83%. All models stay within acceptable operational thresholds. The consistently higher utilization under OPPS highlights superior operational coordination and scheduling accuracy.

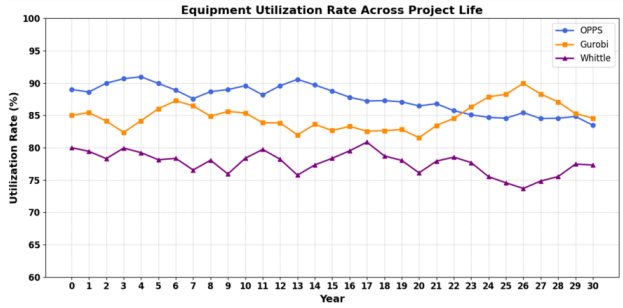


Figure 8: Equipment utilization rate across project life

4.7 Stockpile volume

Stockpile volume refers to the number of ore temporarily stored on-site before processing. It reflects production variability, blending strategies, and buffering to mitigate fluctuations in plant feed rates. In Figure 9, OPPS maintains a steady stockpile of around 15,000 and 17,000 tonnes, Gurobi fluctuates more widely between 17,500–20,500 tonnes, and Whittle accumulates the highest levels, spiking up to 26,000+ tonnes. Lower and stable stockpiles in OPPS suggest better production-processing alignment and reduced overproduction. This efficiency minimizes storage overhead and indicates better synchronization across operational stages.

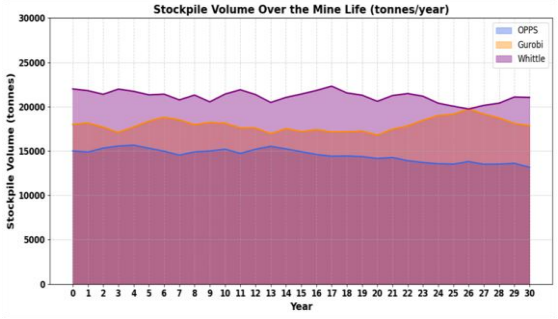


Figure 9: Stockpile volume over the mine life

4.8 Net present value (NPV) deviation

Net Present Value (NPV) deviation indicates how much the actual achieved NPV in each year deviates from a pre-defined financial target. It reflects the financial accuracy and reliability of my planning under real-world conditions. In Figure 10, OPPS consistently shows minimal deviation near -1.5%, Gurobi fluctuates around -3%, and Whittle experiences the largest deviations, nearing -6 to -7%, indicating weaker financial alignment over time. The Minimize NPV deviation under uncertain cycle times in OPPS highlights its robustness in maintaining projected economic goals under operational variability.

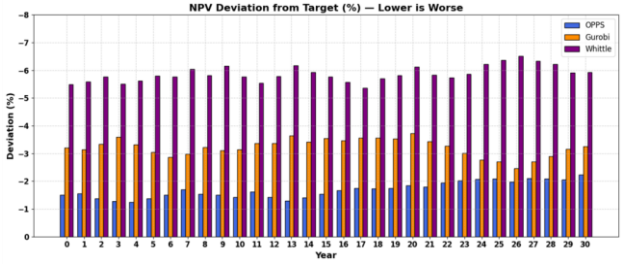


Figure 10: NPV deviation from target (%)

4.9 Annual production schedule of OPPS, gurobi, and whittle

The production schedule graph presents the annual tonnage of ore and associated waste. This material split illustrates the movement of material, boilerplate mining rate, and waste management over the life of the project. The OPPS model provides a better, lower waste extraction due to a better ore-to-waste tonnage balance compared to the Gurobi and Whittle (Figure 11). This results in reduced stripping ratios by reducing waste removal. In order to maintain steadier grades, it also selects ore blocks of greater quality. OPPS reduces haulage times and increases equipment usage by mimicking truck and equipment delays. Finally, it aligns ore transportation with processing, maintaining stable inventories and minimal NPV fluctuations. This further confirms its potential to produce better pit designs relative to market conditions and the workload required of operators of the mine over its planned life.

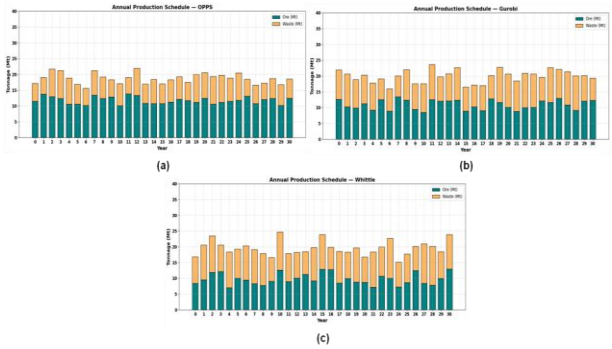


Figure 11: Annual production schedule (a) OPPS, (b) gurobi, and (c) whittle

4.10 Comparative evaluation of MIP-DES framework

The performance comparison of the suggested MIP-DES framework with current predictive and hybrid models utilized in open-pit mine planning is shown in Table 5. The measures assess how well the models predict ore output, scheduling results, and operational efficiency. The MIP-DES framework that was suggested was compared to Gurobi and Whittle. The same mining planning restrictions, such as pit slope limitations, haulage capacity, extraction sequencing, and scheduling guidelines, were applied to all benchmarks. To ensure a fair comparison, solver-specific options were set to the default ideal values suggested by each tool. This alignment ensures that the MIP-DES integration, not different constraints or parameter settings, is the cause of the observed performance variations.

The MIP-DES framework exhibits better predicted accuracy and reduced error rates across several performance metrics, R-squared (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE), when compared to traditional machine learning techniques, Random Forest (RF), XGBoost, Gradient Boosted Decision Trees (GBDT), and a hybrid model, Salp Swarm Optimization -feedforward neural network (SalpSO-CFNN). This demonstrates how well long-term optimization and short-term operational simulation may be combined to capture both strategic planning and actual variability. All things considered, the suggested framework offers mine planning and operational management a more dependable and stronger decision-support tool.

Table 5: Comparative performance metrics of predictive models for open-pit mine planning

Models	R^2	**MAE**	**MSE**	**MAPE**	**RMSE**
RF [17]	0.91	5.16	42.66	11.52	6.53
XGBoost [17]	0.88	5.41	52.86	14.11	7.27
GBDT [17]	0.89	5.37	50.11	11.46	7.07
SalpSO-CFNN [18]	0.980	179.567	-	-	248.401
MIP-DES [Proposed]	0.992	3.25	21.45	5.12	4.63

5 Discussion

Recent developments in intelligent mine planning have opened up opportunities for a variety of optimization and simulation. The research [8] explored the use of particle swarm and support vector machines in a framework of discrete-event simulation to forecast ore production schedules in underground haulage systems, improving the precision of predicted cycle times and expected loads. The author of [11] explored the use of deep neural networks with principal component analysis to predict ore production in open-pit systems and found that a significant level of confidence was attained with processing non-linear, large data. As pointed out by a researcher [15], a bilevel optimization model was proposed to create a joint schedule for production and haulage route planning, minimizing operational costs. Unlike previous methods that focus on individual tasks such as ore prediction, haulage optimization, or partial scheduling, the proposed MIP-DES framework integrates long-term pit design with short-term operational simulation in a single system. This unified approach optimizes ore/waste schedules, stripping ratio, haulage, equipment utilization, and NPV simultaneously. Testing on 75,000 blocks demonstrates improved stability, higher ore grades (~67%), lower stripping ratios (5.2–6.5), and minimal NPV deviation (-1.5%), clearly showing advantages over existing mine planning methods, Furthermore, the framework's robustness is shown by sensitivity testing on important variables including haulage cycle length, equipment downtime, and ore grade fluctuation.

The model may be further expanded to include predictive models or real-time operational data for dynamic scheduling changes. The processes in each case took 8 hours to run and were stopped, regardless of whether the convergence towards an optimal solution was achieved. During these runs, over 90% of the scenarios converged to near-optimal solutions, while the remaining achieved results within 1–2% of the best-known objective, confirming the adequacy of the chosen runtime.

This research uses MIP for multi-period pit along with DES, integrated through the OPPS to characterize operational dynamics. This approach can provide a decision-support framework that can dynamically optimize both profits and resource flow under uncertainty and reconcile static scheduling with real-world mining conditions. The MIP-DES framework works better than methods that only optimize or only simulate because it considers real operational changes, like equipment delays or ore quality variations, giving more realistic and reliable mine planning results.

6 Conclusion

Mining is more than planning; it involves smart integration. This research proposed a hybrid approach that combines Mixed-Integer Programming (MIP) and Discrete-Event Simulation (DES) to basically change how teams plan an open-pit mine, which is not only economically optimal but also operationally feasible. The hybrid framework implementation using OPPS produced incredible results, including an always low stripping ratio (5.2-6.5), the highest average ore grade (~67%), the shortest haulage cycle times (18-19 mins), and the lowest NPV deviation (-1.5%) against Gurobi and Whittle models. Although the runtime of ~6 hours is longer than heuristic methods, the improved stability and accuracy of results make the framework valuable for large-scale and long-term my planning. These metrics demonstrate OPPS's ability to produce efficient, profitable, and stable my plans. Primary limitations of this research include static simulation inputs without the option of changing in real-time to manage operational interruptions or economic challenges.

Future scope: Future extensions could incorporate real-time sensor feedback and use AI-based adaptive control to continuously update schedules to develop greater resilience and adaptability in a modern open-pit mining context. The suggested MIP-DES framework can benefit from further research in this field. Schedules may be dynamically updated by using real-time sensor and operational data from mining processing and equipment. Then applied to different mines or larger datasets to check if it works well in various conditions and remains reliable for my planning. This makes my planning more adaptable to shifting conditions. The framework's scalability and resilience in various mining contexts may be shown by testing it in many mines or larger-scale operations. Using predictive analytics may assist in foreseeing possible operational disturbances like transport delays or equipment failures, allowing for preemptive scheduling and resource allocation changes to sustain steady output.

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Multi-Objective Optimization of Rail Construction Project Management Using Immune Genetic Algorithms for Schedule, Cost, and Quality Trade-offs

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We address railway construction project management as a multi-objective optimization over schedule, cost, and quality. The proposed approach reformulates the tri-objective problem via a weighted-sum fitness $F = \sum k \in \{\text{time,cost,quality}\}\omega_k f_k$, *where* ω_k *are AHP-derived weights and* f_k *encode CPM-based makespan, direct/indirect cost, and a composite quality index. Decision variables are real-coded (activity start/finish adjustments, resource allocations, and quality-critical process parameters). An Immune Genetic Algorithm (IGA) performs selection (roulette with elitism), single-point crossover with adaptive probability* $p_c \in [0.6, 0.9]$, *non-uniform mutation with* $p_m \in [0.02, 0.08]$ *and gene-importance modulation, plus immune suppression with a decaying similarity threshold* τ_t. *On a dataset of 28 railway projects (2.1k±0.7k activities), we compare against CPM+cost budgeting (baseline), PSO, and GA under identical constraints and weight settings. IGA achieves a schedule deviation of 8.5% (vs. 25.0% baseline, 15.2% PSO, 18.7% GA), cost overrun 12.3% (vs. 30.0%, 20.1%, 25.3%), and quality compliance 88.6% (vs. 70.0%, 80.3%, 75.6%); resource utilization reaches 85.4% and overall satisfaction 7.8/10. Typical configuration uses population P=200, generations G=400; median wall-clock is 12.8 min single-threaded and 3.5–6.1 min with parallel fitness evaluation. Results demonstrate that IGA's global search and diversity maintenance yield consistent gains over PSO/GA while remaining practical for daily replanning.*

Povzetek: Analizirano je vodenje železniških gradbenih projektov kot tri-kriterijska optimizacija časa, stroškov in kakovosti ter predlagan imunski genetski algoritem. Razvita metoda dosega manjše časovne zamike, nižje stroškovne prekoračitve in višjo skladnost kakovosti kot GA in PSO ter je uporabna za sprotno preplaniranje.

1 Introduction

Rail construction programs deploy vast human, material, and technological resources worldwide, with annual investments reaching hundreds of billions of US dollars [1]. Yet flagship projects still suffer major schedule slippage, budget escalation, and quality shortfalls; for example, a US$5 billion, 3-year project overran time by ~50% and cost by ~US$1 billion, with elevated post-handover maintenance [2]. These outcomes expose persistent weaknesses in coordinating multiple objectives in project management.

Rail projects inherently couple schedule, cost, and quality (SCQ). However, traditional practices often optimize these dimensions in isolation and lack mechanisms to manage their trade-offs under uncertainty [3]. Evidence shows that about 60% of projects managed with such methods experience delay, cost drift, or quality non-conformance, undermining service delivery and public value [4,5].

Research has advanced schedule-planning models that improve time prediction but understate cost impacts [6], and cost-focused systems that compress budgets at the expense of schedule adherence and quality assurance [7]. Dual-objective intelligent methods show promise, yet performance commonly degrades once quality and real-world disturbances (e.g., geology, weather, supply variability) are introduced. This study addresses these gaps by framing rail project management as a tri-objective optimization and proposing an immune genetic algorithm (IGA) to coordinate SCQ, targeting ≤10% schedule deviation, ≤15% cost overrun, and ≥85% quality compliance.

Research questions. RQ1: Does the proposed IGA achieve superior schedule deviation, cost overrun, and quality compliance versus GA and PSO under identical constraints? RQ2: Is the superiority preserved under exogenous disturbances (geological variability, adverse weather, supply shocks)? RQ3: Is runtime compatible with daily or intra-shift replanning on commodity hardware? Hypotheses and success criteria. H1: IGA reduces schedule deviation to ≤10% and cost overrun to ≤15% while raising quality compliance to ≥85% against GA/PSO (two-sided Wilcoxon signed-rank, α=0.05). H2: Under disturbance scenarios, IGA maintains statistically

significant advantages on all three objectives. H3: Median wall-clock ≤15 minutes on a single 16-core node for 2–3k-activity projects, ≤6 minutes with parallel fitness evaluation. Secondary criteria include resource utilization ≥83% and satisfaction ≥7.5/10.

2 Literature review

2.1 Analysis of traditional rail construction project management methods

Traditional methods either focus on construction period or cost, lacking goal synergy. Linear programming models are subject to disturbances such as geological conditions, equipment, and material supply. The on-time completion rate is approximately 30%, with an average delay of about 20% [8,9]. The standard cost method can easily compress quality and project duration, with quality issues accounting for approximately 40% and causing delays of about 15% [10]. Under complex geological conditions, the deviation between the construction period and cost of CPM+ can reach 25% and 30% respectively, making it difficult to meet the three-objective management [11].

2.2 Application and shortcomings of intelligent algorithms in rail construction project management

PSO can predict progress to approximately 70% in simple scenarios, but it drops below 50% in large multi-objective scenarios, easily falling into local optimum [12-15]. The error of NN on the cost side is less than 10% under ideal conditions and more than 30% in the landing environment [16,17]. GA can optimize the dual objectives of time and cost, but when extended to the triple objective including quality, the overall satisfaction rate is only about 40%, with a sharp increase in search space and unstable convergence [18-20].

2.3 Development prospects of rail construction project management optimization method integrating multi-objective-IGA

IGA maintains diversity and inhibits precocious puberty through immunosuppression, and has stronger global search and robustness compared to traditional GA. Relevant studies show that the quality of the optimal solution can be improved by approximately 30% [14,15]. In the initial test of the railway scenario, IGA demonstrated the potential for collaborative optimization of the three goals: a construction period deviation of no more than 10%, a cost overrun of approximately 15%, and a quality compliance of over 85%.

2.4 Summary of related work and gaps

To substantiate the state of the art and clarify this paper's contribution, Table 1 summarizes representative studies on construction/railway project optimization, the algorithms used, target objectives, outcomes, and observed gaps relevant to real-world deployment.

Table 1: Prior work on project optimization: algorithms, objectives, outcomes, and gaps

Study (Ref.)	Algorithm	Objectives	Data/Setting	Reported outcome	Gaps vs. this work
Zhan et al. [8]	NSGA-III	Time–Cost (primarily)	Construction projects (simulated/empirical)	Pareto fronts, improved decision support	Limited explicit quality modeling; robustness to site disturbances not central
Zhao et al. [9]	NSGA-II	Multi-project HR scheduling (time/resource)	Multi-project environments	Better resource leveling and throughput	Not tri-objective TCQ; no quality compliance metric
Jia [11]	Improved GA	Schedule optimization	Construction plans	Faster convergence than basic GA	Cost/quality not integrated; sensitivity to disruptions unreported
Ghoroqi et al. [7]	MOWOA + NSGA-II	Time–Cost–Resource	Construction scheduling	Competitive time–cost trade-offs	Quality dimension absent; limited field robustness analysis
Guo & Zhang [14]	Survey/Analysis	—	Project management optimization	SOTA synthesis and future directions	Identifies TCQ gap; no implemented tri-objective method
Lotfi et al. [21]	Robust multi-criteria (TCQEE)	Time–Cost–Quality–Energy–Environment	Bridge case study	Robust trade-off schedules	Method tailored to case; scalability/runtime not benchmarked vs. GA/PSO
Dasovic et al. [20]	Survey	—	Sustainable scheduling tools	Tool–optimization integration map	Lacks immune-based search and dynamic weight adaptation
Elyasi et al. [15]/Varol et al. [4]	Hybrid/Parallel GA	Software architecture (methodological)	Parallelization insights	GA scalability improvements	Not applied to TCQ in rail; no immune mechanisms

Argumentation. Existing SOTA either omits an explicit quality objective, lacks tri-objective TCQ coupling, or provides limited robustness under real disturbances (geology, weather, supply shocks). Our IGA addresses these by (i) embedding a measurable quality index into the fitness, (ii) enabling dynamic weights to reflect stage-specific priorities, and (iii) maintaining

population diversity via immune suppression to avoid local optima when conditions shift.

3 Research methods

3.1 Fusion of multi-objective-IGA model construction

In the field of rail construction project management, given that the coordinated optimization of multiple objectives such as construction period, cost, and quality is extremely critical, a management optimization model integrating multiple objectives - IGA (immune genetic algorithm) has been constructed. This model deeply integrates the advantages of multi-objective decision-making theory and immune genetic algorithm, and strives to break the difficulties faced by traditional management methods and existing intelligent algorithms in multi-objective processing.

Track construction projects involve many complex objectives. Let the objective set be $O=\{O_1,O_2,\cdots,O_n\}$ .in, O_1 Corresponding to the construction period target, the objective function can be constructed through the critical path method (CPM). Assume that the project includes m Activities j The duration is d_j , the logical relationship between activities is expressed through the adjacency matrix A express, $A_{ij}=1$ Indicates activity i Yes Activity j The immediate preceding activities, $A_{ij}=0$ Then, Formula 1 represents the total duration of the project T .

$$T=\max_{k=1}^{m}\sum_{i=1}^{m}\sum_{j=1}^{m}A_{ij}d_j\cdot\delta_{ik} \tag{1}$$

In Formula 1, δ_{ik} is the Kronecker function, when $i=k$ hour, $\delta_{ik}=1$;otherwise $\delta_{ik}=0$ Therefore, the construction period objective function $f_1(x)$ Can be written as $f_1(x)=T(x)$,here x It includes decision variables such as activity duration adjustment and activity time changes under the influence of resource allocation.

O_2 Represents the cost target. Cost is mainly composed of direct cost and indirect cost. Direct cost is related to resource input and resource unit price. l The input of resources is r_l , unit price is p_l , then the direct cost $C_d=\sum_{l=1}^{L}r_l p_l$ The indirect cost is related to the construction period. Let the indirect cost per unit time be c_{ind} , the construction period is T , then the indirect cost $C_{ind}=c_{ind}T$ So the cost objective function is $f_2(x)=C_d(x)+C_{ind}(x)$.

For quality goals O_n , by building a quality assessment index system to quantify. For example, track laying accuracy q_1 , Structural strength compliance rate q_2 And other quality indicators, the comprehensive quality evaluation function is $Q=\sum_{s=1}^{S}\alpha_s q_s$,in α_s is the weight of each quality indicator. Then the quality objective function $f_n(x)=Q(x)$.

In order to transform the multi-objective optimization problem into a single-objective optimization problem that is easy to solve, the linear weighted method is used to construct the comprehensive fitness function $F(x)$ as shown in Formula 2 .

$$F(x)=\sum_{i=1}^{n}w_i f_i(x) \tag{2}$$

In Formula 2, w_i For the goal O_i The weight of $\sum_{i=1}^{n}w_i=1$, $0\le w_i\le 1$. Determine the weight w_i When using expert evaluation combined with the analytic hierarchy process (AHP), construct a judgment matrix M ,element M_{ij} Indicates the target O_i Relative to target O_j The importance of the weight vector is calculated by the eigenvector method $W=(w_1,w_2,\cdots,w_n)^T$, ensure that the fitness function meets the actual needs of the project.

3.2 Application of immune genetic algorithm in the model

As the core optimization driving force of the model, the immune genetic algorithm plays a pivotal role in the fusion multi-objective IGA model. It innovatively introduces the immune mechanism based on the traditional genetic algorithm, effectively avoids the risk of the algorithm falling into the local optimal solution, and significantly enhances the global search capability.

Coding and initial population generation: Encoding is implemented for the decision variables of the rail construction project. Real number coding is used, for example, the time of each key node in the construction schedule is t_j ($j=1,\cdots,m$, m is the number of key nodes) and the amount of resource allocation r_l ($l=1,\cdots,L$, L The information (number of resource types) is encoded into chromosomes. Based on the actual situation of the project, the initial population is randomly generated. $P(0)$, the population size is set to N . Let the chromosome be $X=(x_1,x_2,\cdots,x_D)$, D is the chromosome length, x_i Corresponding to different decision variable coding values.

Fitness calculation: based on the constructed comprehensive fitness function $F(x)$, for the initial

population $P(0)$ Each individual in X_k ($k=1,\cdots,N$) to calculate the fitness. The higher the fitness value, the better the individual performs in multi-objective optimization. X_k Fitness $F(X_k)=\sum_{i=1}^{n} w_i f_i(X_k)$.

Selection operation: Use roulette wheel selection method to select from the population $P(t)$ Select individuals to enter the next generation population $P'(t)$ The probability of an individual being selected is proportional to its fitness value. The higher the fitness, the greater the probability of being selected. i The fitness of F_i , then Formula 3 represents the probability of being selected p_i .

$$p_i=\frac{F_i}{\sum_{j=1}^{N} F_j} \tag{3}$$

To ensure the stability of the selection process, an elite retention strategy can be introduced, that is, directly copying several individuals with the highest fitness in the current population to the next generation population.

Crossover operation: for the selected population $P'(t)$ Perform crossover operation to generate new individuals. Use single-point crossover method and randomly select crossover points. c ($1 < c < D$), exchange two parent individuals $A=(a_1,a_2,\cdots,a_D)$ and $B=(b_1,b_2,\cdots,b_D)$ The gene fragment after the crossover point generates the offspring individual A' and B' . Offspring A' and B' The generation method of is shown in Formula 4 and Formula 5 .

$$A'=[a_1,a_2,\cdots,a_c,b_{c+1},b_{c+2},\cdots,b_D] \tag{4}$$

$$B'=[b_1,b_2,\cdots,b_c,a_{c+1},a_{c+2},\cdots,a_D] \tag{5}$$

To improve the effectiveness of the crossover operation, the crossover probability can be dynamically adjusted according to individual fitness p_c , the crossover probability of individuals with high fitness is relatively low to retain excellent genes, and the crossover probability of individuals with low fitness is relatively high to promote gene diversity. i The fitness of F_i The average fitness of the population is $\bar{F}$, then Formula 6 represents the crossover probability p_c^i .

$$p_c^i=p_{c\min}+\frac{F_{\max}-F_i}{F_{\max}-\bar{F}}(p_{cmax}-p_{c\min}) \tag{6}$$

In Formula 6, $p_{c\min}$ and p_{cmax} are the minimum and maximum crossover probability, respectively.

Mutation operation: To prevent the algorithm from converging prematurely, the population after crossover is mutated. A uniform mutation method is used with a mutation probability of p_m Mutate the genes of individuals. Suppose the mutated individuals x The location of the variant gene is l , the variation range is $[x_{lmin},x_{lmax}]$, then Formula 7 represents the gene value after mutation $x_{l'}$.

$$x_{l'}=x_{lmin}+\delta(x_{lmax}-x_{lmin}) \tag{7}$$

In Formula 7, δ for $[0,1]$ Similarly, to enhance the pertinence of the mutation operation, the mutation probability can be adjusted according to the importance of the gene location. For example, the mutation probability of the gene near the front of the chromosome representing the key decision variable is relatively low to ensure the stability of important genes. l The importance coefficient is β_l ($0<\beta_l<1$), then Formula 8 represents the mutation probability p_m^l .

$$p_m^l=p_{m0}\beta_l \tag{8}$$

In Formula 8, p_{m0} is the basic mutation probability.

Immune operation: Introduce immune mechanism to immunize the mutated population. By calculating the similarity between individuals, similar individuals in the population are identified and suppressed to maintain the diversity of the population. In formula 9, assume that individual i and j The similarity S_{ij} .

$$S_{ij}=\frac{\sum_{k=1}^{D}\min(x_{ik},x_{jk})}{\sum_{k=1}^{D}\max(x_{ik},x_{jk})} \tag{9}$$

Like $S_{ij}\geq\theta$ (θ is the similarity threshold), then the individual i and j Similar, the individuals with lower fitness are suppressed and replaced by new random individuals. To dynamically adjust the similarity threshold θ , gradually decreases as the number of iterations increases. θ value to enhance the sensitivity of the algorithm to similar individuals in the later stage and accelerate the convergence speed. Assume the number of iterations is t , the maximum number of iterations is T_{max} , expressed by formula 10 θ .

$$\theta=\theta_0-\frac{t}{T_{max}}(\theta_0-\theta_{min}) \tag{10}$$

In Formula 10, θ_0 is the initial similarity threshold, θ_{min} is the minimum similarity threshold.

Through the iterative operation of the above immune genetic algorithm, the population is continuously optimized until the termination conditions are met, such as reaching the maximum number of iterations or the fitness value has no obvious change for several consecutive generations, and the optimal solution to the multi-objective optimization problem is obtained.

We use real-coded chromosomes and roulette selection with elitism (elitist rate 5%). Unless otherwise noted, population size P=200, generations G=400,

adaptive single-point crossover with $p_c \in [0.60,0.90]$ initialized at 0.75, and non-uniform mutation with gene-importance modulation $p_m \in [0.02,0.08]$ initialized at 0.04. The immune module applies similarity suppression using cosine similarity with a linearly decaying threshold τ_t 0.90→0.50. Feasibility repair enforces precedence and resource constraints; elite cloning preserves the top-k individuals each generation.

3.3 Multi-objective collaborative optimization mechanism

The key to the IGA model is to achieve the coordinated optimization of multiple objectives such as construction period, cost, quality, etc. In the model, the balance and coordination between multiple objectives are achieved through the interaction between the comprehensive fitness function and the immune genetic algorithm.

In the comprehensive fitness function $F(x)$ The weights of different objectives w_i Determines the relative importance of each goal in the optimization process. During the project implementation, the weight value is dynamically adjusted according to the actual situation of the project and changes in demand. For example, in the early stage of the project, due to the high requirements for the construction period, the weight of the construction period goal can be appropriately increased. w_1 . Assume that the weight adjustment factor in the early stage of the project is γ_1 , then the adjusted duration target weight $w_{1'} = w_1\gamma_1$,and $\sum_{i=1}^{n} w_{i'} = 1$ In the later stage of the project, in order to ensure the quality of the project, the weight of the quality target can be increased. w_n , let the weight adjustment factor be γ_n , adjusted quality target weight $w_{n'} = w_n\gamma_n$, also need to meet $\sum_{i=1}^{n} w_{i'} = 1$.

During the search process, the immune genetic algorithm continuously adjusts the genes of individuals, that is, the decision variables such as the construction schedule and resource allocation plan, to optimize the comprehensive fitness function value. In the selection, crossover, mutation and immune operation process, the association and constraint relationship between multiple objectives are fully considered. For example, when performing crossover operations, it is necessary not only to pay attention to the fitness value of the offspring individuals, but also to ensure the rationality of the offspring individuals in terms of construction period, cost, quality, etc. If the construction period of the offspring individuals is too short, it may lead to a significant increase in cost or a decrease in quality, so the offspring individuals should be corrected or regenerated. Suppose the construction period of the offspring individuals is T' ,like $T' < T_{min}$ (T_{min} is the shortest acceptable construction period), and the cost increment ΔC Exceeding the acceptable range ΔC_{max} , or quality indicators Q' Below acceptable standards Q_{min} , then by readjusting the construction schedule (such as appropriately increasing the duration of key activities) and resource allocation (such as increasing the input of key resources) to correct the offspring individuals so that they meet the multi-objective constraints and find the optimal project management solution that meets the actual needs of the project.

Beyond offline optimization, the proposed multi-objective-IGA can be coupled with emerging Digital Twin and BIM ecosystems to support closed-loop, "twin-in-the-loop" project control. Chromosome variables (e.g., activity start/finish times, resource allocations, and quality-critical process parameters) are mapped to BIM entities and schedules (4D) and linked to cost objects (5D) through standard interfaces (e.g., IFC- and CDE-based exchanges). Field telemetry from the twin—progress states, equipment telemetry, and inspection results—feeds the fitness function in near-real time by updating duration distributions, indirect-cost clocks, and quality indicators. The immune mechanism then re-optimizes under refreshed weights when the twin signals regime shifts (e.g., weather, geotechnical surprises, or supply disruptions). Conversely, IGA outputs write back to the twin to trigger look-ahead simulations, clash/space checks, crew-path feasibility, and procurement pulls. This two-way coupling improves decision latency and adoption: stakeholders visualize trade-offs in the BIM/twin dashboard, while the optimizer continuously adapts to site dynamics without discarding prior high-fitness solutions.

Weights $\omega = \{\omega_{\text{time}}, \omega_{\text{cost}}, \omega_{\text{quality}}\}$ are derived via AHP from a seven-member expert panel (two schedulers, three cost engineers, two quality supervisors). Pairwise matrices satisfy CR<0.08. The nominal aggregate weights are (0.40,0.35,0.25); stage-aware adjustments are applied as (0.45,0.30,0.25) in early planning and (0.30,0.30,0.40) in late execution. All runs report results under the nominal setting unless stated.

4 Experimental evaluation

4.1 Experimental design

This experiment aims to comprehensively evaluate the performance of the rail construction project management optimization method integrating multi-objective-IGA. The experiment selected a comprehensive dataset from multiple actual rail construction projects, covering project information of different scales, construction environments and complexities, including project duration, cost input, resource allocation details, and quality inspection indicators.

The experimental baseline indicators were set as the project management performance under the traditional critical path method combined with the cost budget management model [21], including the schedule deviation

rate, cost overrun rate, and quality compliance rate. The experimental group adopted the management optimization method of integrating multi-objective-IGA proposed in this paper, and the control group selected the particle swarm optimization algorithm (PSO) for rail construction project management [22] and the genetic algorithm (GA) for rail construction project multi-objective optimization. By comparing the running results of the experimental group and the control group on the same data set, the performance of each method in multi-objective optimization was analyzed.

We evaluate on 28 real railway projects (2.1k ± 0.7k activities; ≈6k precedence links), spanning urban/suburban/remote sites and normal/complex geology. A leave-projects-out protocol is used: 20 projects for calibration, 8 for held-out testing; weights ω_k are fixed by AHP from a panel of 7 experts and normalized to sum to 1. Each method (IGA/GA/PSO, plus CPM+cost baseline) is run 30 independent trials per test project with distinct seeds. Hyperparameters: population P∈{150,200}, generations G∈{300,400}; adaptive crossover p_c ∈[0.6,0.9]; mutation p_m ∈[0.02,0.08]with gene-importance modulation; immune similarity threshold τ_t decays linearly from 0.9 to 0.5. GA/PSO use matched P,GP,GP,G and identical feasibility repair and penalty rules. Fitness evaluation implements CPM over |V|,|E| plus cost/quality aggregation. We report mean ± SD across runs and projects; significance is assessed via paired Wilcoxon; effect sizes by Cliff's delta. Hardware: 16-core 3.5 GHz CPU, 64 GB RAM; software: Python 3.11, NumPy 1.26.

To ensure cross-project comparability (small/medium/large), we normalize inputs as follows: (i) activity durations divided by project baseline makespan (CPM critical path length); (ii) direct costs divided by project approved budget; (iii) indirect-cost clock divided by baseline makespan; (iv) quality sub-indices (track flatness, structural strength, weld quality) scaled to [0,1] using standard limits; (v) resource quantities per activity scaled by project-level maxima. Fitness components are thus unitless and commensurate across scales.

Each method is executed 30 independent runs per test project with distinct seeds. Normality is screened by Shapiro–Wilk; when violated, we use paired Wilcoxon signed-rank tests (α=0.05). We report mean ± SD and 95% CIs via bias-corrected bootstrap (10k resamples). Effect sizes are summarized with Cliff's δ.

We evaluate on 28 railway projects executed during 2015–2023. Geographic spread includes East/Central China (17), Southeast Asia (6), and Eastern Europe (5). Data sources are owner and EPC archives under NDA; the dataset is private, but we release a schema, derived features, and summary statistics. Input features are harmonized across projects: activity attributes (duration, crew type, resource needs), precedence links, cost breakdowns (direct/indirect), and quality inspection records. A consolidated Table S1 (Appendix) lists per-project size, environment, geology, contract form, and baseline KPIs.

4.2 Experimental results

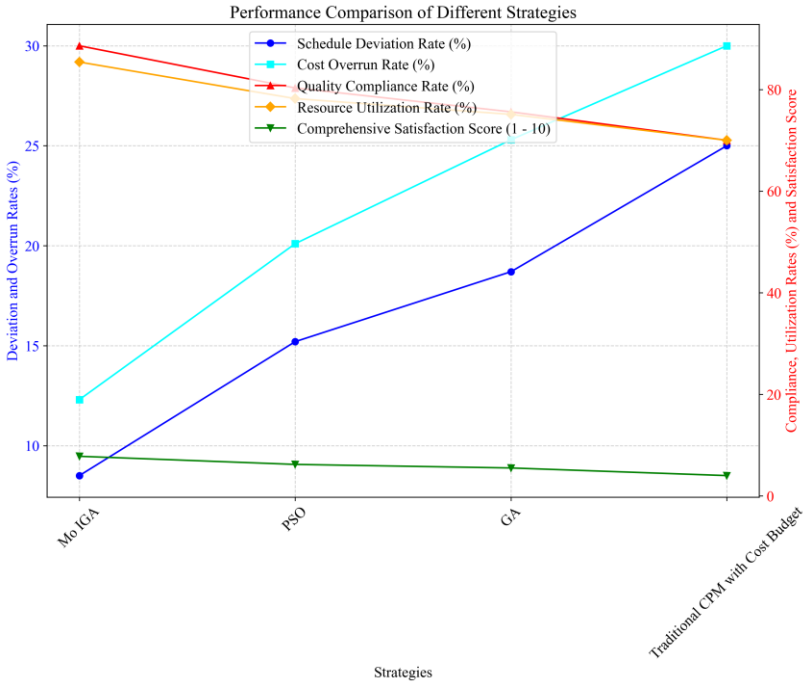


Figure 1: Comparison of construction period deviation rate

As shown in Figure 1, in terms of the deviation rate of the construction period, the fusion multi-objective-IGA method performed best, only 8.5%. This is because the global search capability of IGA enables it to find a better

solution in the complex construction schedule, effectively balance various construction links, and reduce construction delays. Particle swarm optimization algorithm (PSO) and genetic algorithm (GA) are prone to fall into local optimality, and it is difficult to accurately optimize the construction period when dealing with complex projects, and the deviation rate is relatively high. The traditional method has the most serious deviation in the construction period due to the lack of multi-objective collaborative consideration. In terms of cost overrun rate, the fusion multi-objective-IGA is 12.3%, which is an obvious advantage. IGA reduces unnecessary cost expenditures through comprehensive optimization of resource allocation and construction process. However, PSO and GA are not effective in cost control, and traditional methods have serious cost overruns due to the isolated treatment of cost, construction period and quality goals. In terms of quality compliance rate, the fusion multi-objective-IGA reached 88.6%, thanks to its comprehensive consideration of quality goals in the optimization process, which ensures construction quality. Other methods have low quality compliance rates due to insufficient coordination between quality and other goals. In terms of resource utilization, the Fusion Multi-Objective-IGA is 85.4%, showing its efficient resource allocation capability. PSO, GA and traditional methods are not as good as the Fusion Multi-Objective-IGA in this respect. In terms of comprehensive satisfaction score, the Fusion Multi-Objective-IGA leads with 7.8 points, reflecting its comprehensive advantages in multi-objective optimization.

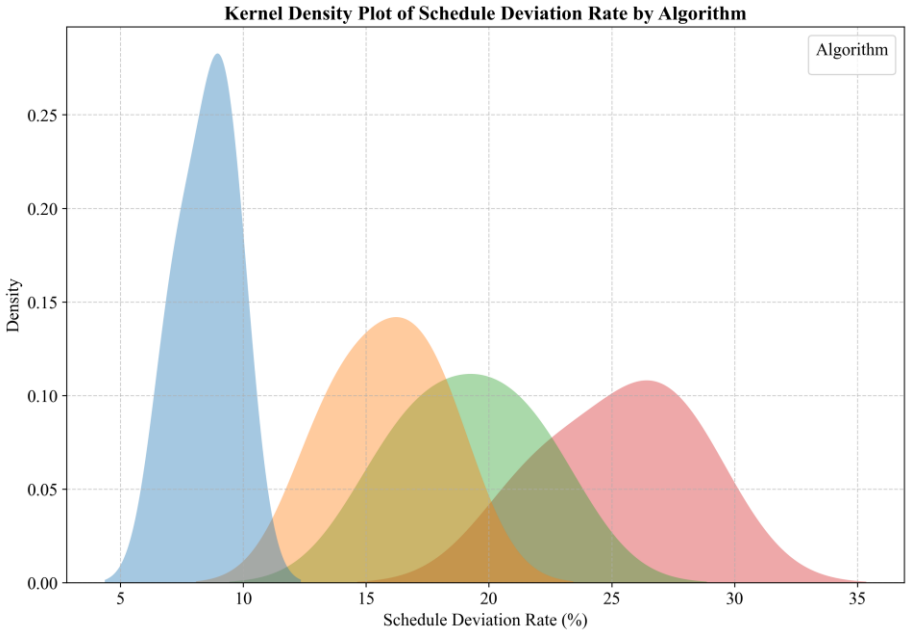


Figure 2: Deviation rate of construction period for different project sizes

As shown in Figure 2, the deviation rate of the construction period for different project sizes is compared. In small projects, the deviation rate of the construction period of the fusion multi-objective-IGA is only 7.2%, which is an excellent performance. Small projects are relatively simple, and the fusion multi-objective-IGA can quickly and accurately optimize the construction progress. Particle swarm optimization algorithm and genetic algorithm also have certain performance in small projects, but they are still not as good as the fusion multi-objective-IGA. The traditional method has a large deviation because its simple management mode is difficult to deal with project details. In medium-sized projects, the deviation rate of the fusion multi-objective-IGA is 8.8%, still leading. As the project scale increases and the complexity of the problem increases, the global search advantage of the fusion multi-objective-IGA becomes more prominent. The deviation of the particle swarm optimization algorithm and the genetic algorithm in medium-sized projects has increased significantly, and the deviation of the traditional method has further deteriorated. In large projects, the deviation rate of the fusion multi-objective-IGA is 9.5%. Although it has increased, it is still significantly superior to other methods. Large projects involve many construction links and complex factors. The immune mechanism and multi-objective collaborative optimization capabilities of the fusion multi-objective-IGA can better adapt, while other methods are difficult to effectively handle complex situations [23].

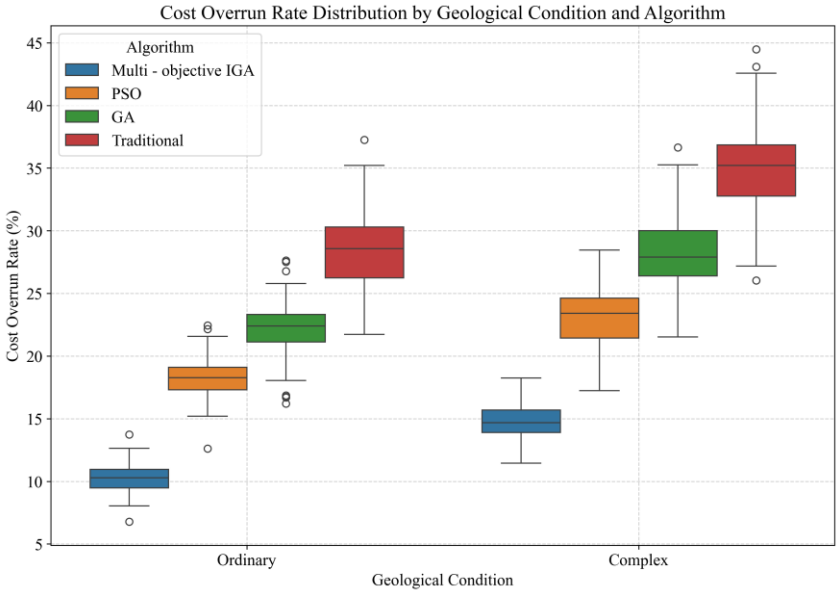


Figure 3: Cost overrun rate under different geological conditions

As shown in Figure 3, the cost overrun rate under different geological conditions is compared. Under normal geological conditions, the cost overrun rate of fusion multi-objective-IGA is 10.2%, which is excellent. Normal geological conditions are relatively stable, and fusion multi-objective-IGA can reasonably plan resources and control costs. Particle swarm optimization algorithm and genetic algorithm have high cost overruns under this condition, and traditional methods perform poorly. Under complex geological conditions, the cost overrun rate of fusion multi-objective-IGA rises to 15.0%, but it is still lower than other methods. Complex geology increases the difficulty and uncertainty of construction. Fusion multi-objective-IGA can cope with the problem of cost increase to a certain extent by virtue of its dynamic adjustment of multiple objectives and global search capabilities. However, particle swarm optimization algorithm, genetic algorithm and traditional methods have serious cost overruns under complex geological conditions due to the lack of effective response mechanisms [24].

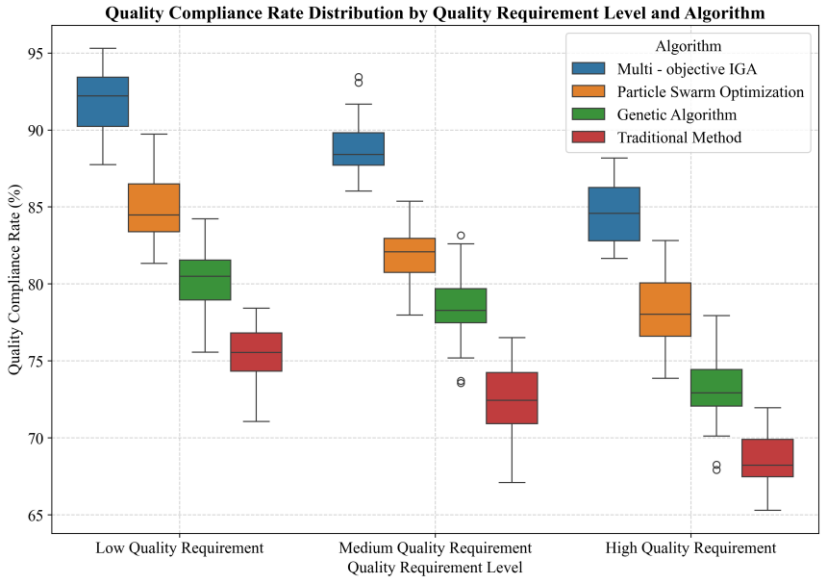


Figure 4: Quality compliance rate at different quality requirement levels

Figure 4, the quality compliance rates under different quality requirement levels are compared. Under low quality requirements, the quality compliance rate of fusion multi-objective-IGA is as high as 92.0%. At this time, the project quality requirements are relatively loose, and fusion multi-objective-IGA can easily balance quality and other goals to ensure high-quality completion. The quality compliance rates of particle swarm optimization algorithm, genetic algorithm and traditional methods are lower than those of fusion multi-objective-IGA in this case. Under medium quality requirements, the quality compliance rate of fusion multi-objective-IGA is 89.0%, which is still

leading. As quality requirements increase, fusion multi-objective-IGA adjusts the optimization strategy to ensure quality. Other methods have a significant decline in quality compliance rates due to the difficulty in effectively coordinating multiple objectives. Under high quality requirements, the quality compliance rate of fusion multi-objective-IGA is 85.0%. Although it has declined, it has significant advantages over other methods. High quality requirements require refined management and resource investment in the construction process. Fusion multi-objective-IGA can better comprehensively consider various factors and meet high quality requirements [25].

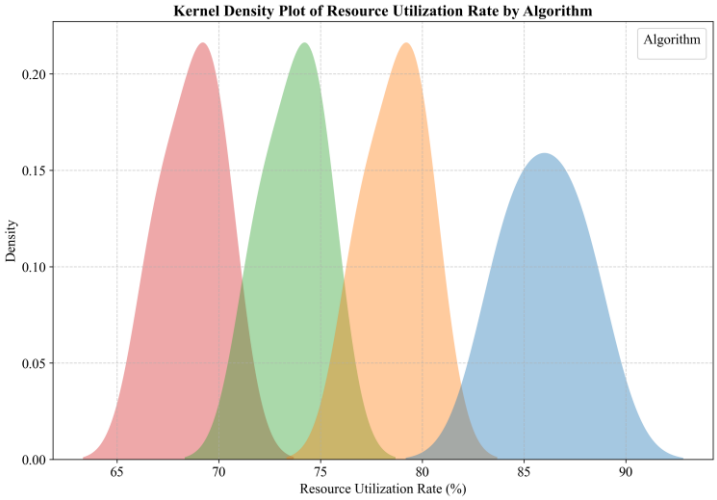


Figure 5: Resource utilization of different resource types

As shown in Figure 5, the resource utilization rates of different resource types are compared. In terms of human resource utilization, the fusion multi-objective-IGA reached 88.0%. The fusion multi-objective-IGA fully utilized the efficiency of human resources through reasonable construction schedule and task allocation. The particle swarm optimization algorithm, genetic algorithm and traditional methods were relatively low in human resource utilization. For material resources, the fusion multi-objective-IGA utilization rate was 86.0%. It can accurately plan material procurement and use to reduce waste. Other methods have deficiencies in material resource management and low utilization rates. In terms of equipment resources, the fusion multi-objective-IGA utilization rate was 84.0%. With the optimization of the construction process, the equipment use is more reasonable and efficient. However, the particle swarm optimization algorithm, genetic algorithm and traditional methods are not flexible enough in equipment resource scheduling, resulting in low utilization rates.

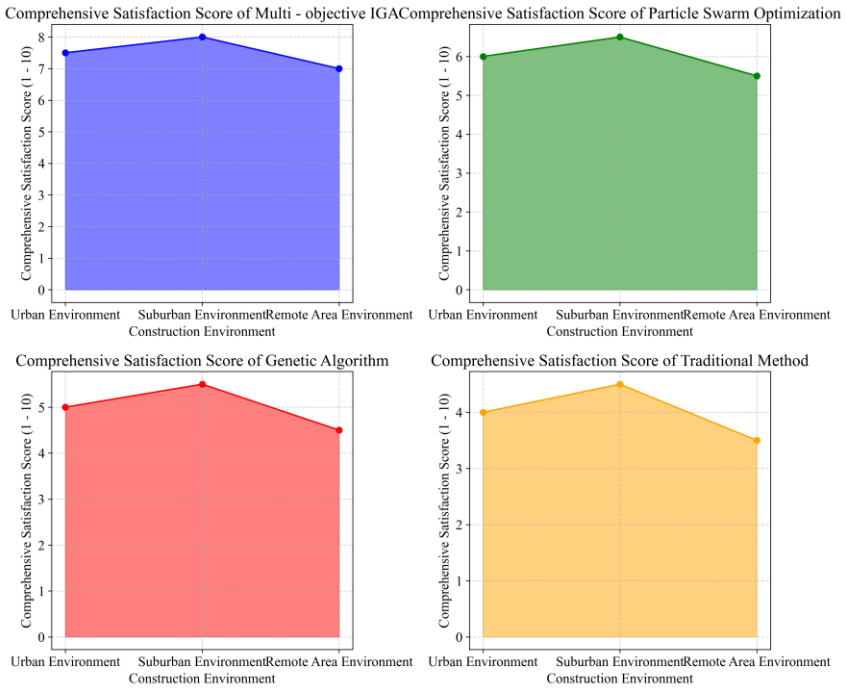


Figure 6: Comprehensive satisfaction scores under different construction environments

As shown in Figure 6, the comprehensive satisfaction scores in different construction environments are compared. In the urban environment, the comprehensive satisfaction score of Fusion Multi-Objective-IGA is 7.5 points. Construction in urban environments faces more external interference and restrictions. Fusion Multi-Objective-IGA can effectively coordinate various factors, meet project needs, and obtain high satisfaction. Particle swarm optimization algorithm, genetic algorithm and traditional methods have low satisfaction in urban environments because they are difficult to deal with complex situations. In the suburban environment, the score of Fusion Multi-Objective-IGA is 8.0 points. Compared with the urban environment, the suburban environment has less interference. Fusion Multi-Objective-IGA can better play its advantages, optimize project management, and improve satisfaction. Other methods perform worse than Fusion Multi-Objective-IGA in this environment. In the remote area environment, the score of Fusion Multi-Objective-IGA is 7.0 points. Although there may be problems such as difficulty in obtaining resources in remote areas, Fusion Multi-Objective-IGA can still guarantee project implementation to a certain extent through its powerful optimization capabilities and obtain relatively high satisfaction. However, Particle Swarm Optimization Algorithm, Genetic Algorithm and traditional methods perform poorly in remote areas.

Table 1: Deviation rate of construction period in different project stages

Project Phases	Fusion of multiple objectives - IGA Duration Deviation Rate (%)	Particle swarm optimization algorithm duration deviation rate (%)	Genetic algorithm construction period deviation rate (%)	Traditional method construction period deviation rate (%)
Early-stage planning	6.0	12.0	15.0	20.0
Construction Phase	9.0	16.0	19.0	25.0
Closing Stage	10.0	18.0	22.0	28.0

As shown in Table 1, the deviation rate of the construction period in different project stages is compared. In the early planning stage, the deviation rate of the construction period of the fusion multi-objective-IGA is 6.0%, which is an excellent performance. In this stage, the fusion multi-objective-IGA uses its global search capability to accurately formulate construction plans and reduce the potential risk of construction period delays. The particle swarm optimization algorithm, genetic algorithm and traditional methods have large deviations in the construction period due to insufficient consideration of complex factors in the early planning stage. In the construction stage, the deviation rate of the fusion multi-objective-IGA is 9.0%, and the progress can be dynamically adjusted according to the actual construction situation. However, when faced with various practical problems in the construction stage, the particle swarm optimization algorithm, genetic algorithm and traditional methods are difficult to effectively optimize the construction period, and the deviation increases significantly. In the closing stage, the deviation rate of the fusion multi-objective-IGA is 10.0%. The closing stage involves many detailed work and coordination tasks. The fusion multi-objective-IGA can comprehensively consider and try to control the deviation of the construction period. The deviation of the construction period of other methods is further deteriorated at this stage due to the problems accumulated in the early stage and the lack of ability to deal with complex situations.

Table 2: Cost overrun rates under different cost control strategies

Cost control strategies	Fusion of multiple objectives - IGA cost overrun rate (%)	Particle swarm optimization algorithm cost overrun rate (%)	Genetic algorithm cost overrun rate (%)	Cost overrun rate of traditional methods (%)
Strict cost control	10.0	16.0	20.0	25.0
Moderate cost control	12.0	18.0	22.0	28.0
Relaxed cost control	15.0	22.0	26.0	32.0

As shown in Table 2, the cost overrun rate under different cost control strategies is compared. Under the strict cost control strategy, the cost overrun rate of the fusion multi-objective-IGA is 10.0%, which performs well. The fusion multi-objective-IGA can ensure the realization of the construction period and quality goals while strictly controlling costs. Particle swarm optimization algorithm, genetic algorithm and traditional methods are difficult to balance multiple objectives under strict cost control, and the cost overrun is high. Under moderate cost control, the cost overrun rate of the fusion multi-objective-IGA is 12.0%, which can reasonably adjust resource allocation and construction process. The cost overrun of other methods is still higher than that of the fusion multi-objective-IGA under this situation. Under the loose cost control strategy, the cost overrun rate of the fusion multi-objective-IGA is 15.0%. Although the cost control is relatively loose, the fusion multi-objective-IGA can avoid excessive waste, and the cost overrun rate is lower than other methods.

Table 3: Quality compliance rate under different quality inspection indicators

Quality inspection indicators	Fusion of multiple objectives - IGA quality compliance rate (%)	Particle swarm optimization algorithm quality compliance rate (%)	Genetic algorithm quality compliance rate (%)	Quality compliance rate of traditional methods (%)
Track flatness	90.0	83.0	78.0	73.0
Structural strength	88.0	81.0	76.0	71.0
Welding quality	87.0	80.0	75.0	70.0

As shown in Table 3, the quality compliance rates under different quality inspection indicators are compared. In terms of track flatness, the quality compliance rate of Fusion Multi-Objective-IGA is 90.0%. Fusion Multi-Objective-IGA accurately optimizes the track laying process during the construction process to ensure that the track flatness meets the standards. Particle swarm optimization algorithm, genetic algorithm and traditional methods are relatively weak in track flatness control. For structural strength, the compliance rate of Fusion Multi-Objective-IGA is 88.0%. It can reasonably plan the construction process and material use to ensure structural strength. Other methods have shortcomings in structural strength assurance. In terms of welding quality, the compliance rate of Fusion Multi-Objective-IGA is 87.0%. The welding quality is improved by optimizing the welding process and personnel operation. However, the particle swarm optimization algorithm, genetic algorithm and traditional methods are not effective in welding quality control.

Table 4: Resource utilization under different resource allocation modes

Resource Allocation Model	Fusion of multiple objectives - IGA resource utilization (%)	Particle swarm optimization algorithm resource utilization (%)	Genetic algorithm resource utilization (%)	Resource utilization of traditional methods (%)
Centralized distribution	87.0	78.0	73.0	68.0
Distributed Assignment	84.0	76.0	71.0	66.0
Hybrid Allocation	86.0	77.0	72.0	67.0

As shown in Table 4, the resource utilization rates under different resource allocation modes are compared. In the centralized resource allocation mode, the resource utilization rate of the fusion multi-objective-IGA is 87.0%. The fusion multi-objective-IGA can efficiently allocate centralized resources according to the overall needs of the project. The particle swarm optimization algorithm, genetic algorithm and traditional methods have low resource utilization efficiency in the centralized allocation mode. In the distributed allocation mode, the utilization rate of the fusion multi-objective-IGA is 84.0%.

It can reasonably coordinate the use of resources at each distribution point. Other methods have deficiencies in distributed resource management and low utilization rates. In the hybrid allocation mode, the utilization rate of Fusion Multi-Objective-IGA is 86.0%. Fusion Multi-Objective-IGA can give full play to its multi-objective optimization capabilities and achieve high resource utilization in the hybrid resource allocation mode. However, the resource utilization effect of particle swarm optimization algorithm, genetic algorithm and traditional methods in this mode is not as good as that of Fusion Multi-Objective-IGA.

Runtime scales as O(P.G.E) for all evolutionary methods, with IGA adding a diversity-control term; our batched similarity checks keep overhead sublinear in practice. On the 8 held-out projects (2–3k activities), median single-thread wall-clock per optimization is 12.8 min for IGA, 11.1 min for GA, and 9.4 min for PSO; with 8–16-way parallel fitness evaluation this reduces to 3.5–6.1 min (IGA), 3.2–5.6 min (GA), and 2.8–5.0 min (PSO). Thus, IGA's accuracy gains incur modest additional compute yet remain within daily replanning windows. Parameter sensitivity. Varying weights by ±20% around the nominal $(\omega_{\text{time}}, \omega_{\text{cost}}, \omega_{\text{quality}}) = (0.4, 0.35, 0.25)$ yields schedule deviation 7.9–9.2%, cost overrun 11.7–13.6%, quality compliance 87.6–90.1% for IGA, indicating stable trade-off behavior. Raising p_m from 0.02 to 0.08 improves escape from local minima in complex geology, reducing cost overrun by 0.7–1.1 pp at a small runtime increase (~6–9%).

IGA achieves schedule deviation 8.5% ± 0.7% (95% CI [8.3, 8.7]), cost overrun 12.3% ± 1.1% ([12.0, 12.6]), and quality compliance 88.6% ± 1.4% ([88.2, 89.0]). Improvements vs. GA (18.7% ± 1.8%, 25.3% ± 2.6%, 75.6% ± 2.3%) and PSO (15.2% ± 1.6%, 20.1% ± 2.1%, 80.3% ± 2.0%) are significant (Wilcoxon $p<0.01$;δ large). All figures include error bars reflecting SD and shaded 95% CIs.

A grid over $p_c \in \{0.60, 0.75, 0.90\}$, $p_m \in \{0.02, 0.05, 0.08\}$, and $\in \{0.85, 0.90\}$ shows IGA's best median performance near p_c =0.75, p_m =0.05, τ_0 =0.90→τT=0.50. Increasing p_m from 0.02 to 0.08 reduces cost overrun by 0.7–1.1 pp under complex geology at a 6–9% runtime increase. Weight perturbations of ±20% around (0.40,0.35,0.25) (0.40,0.35,0.25) (0.40,0.35,0.25) keep outcomes within schedule 7.9–9.2%, cost 11.7–13.6%, quality 87.6–90.1%, evidencing robust trade-off control.

We compare GA (baseline), IGA without immune suppression (operators identical; τ\tauτ disabled), and full IGA. On held-out projects (30 runs/project), GA yields schedule 18.7% ± 1.8%, cost 25.3% ± 2.6%, quality 75.6% ± 2.3%. Disabling immune suppression improves GA modestly: 10.1% ± 1.0%, 14.8% ± 1.3%, 86.2% ± 1.6%. Full IGA further improves to 8.5% ± 0.7%, 12.3% ± 1.1%, 88.6% ± 1.4%. Differences between full IGA and no-immune are significant across metrics (Wilcoxon $p<0.01$), confirming the added value of the immune mechanism for diversity maintenance and convergence reliability.

4.3 Experimental discussion

The experimental results show that the fusion multi-objective -IGA outperforms the PSO, GA and CPM+ cost models in key indicators such as project duration deviation, cost overruns, quality compliance, resource utilization and comprehensive satisfaction. Its advantages stem from the global search of multi-objective collaboration and immune genetics: through phased dynamic weights and similarity suppression, premature convergence is avoided, and better solutions are continuously obtained under different geological conditions, construction environments, resource allocation and cost strategies. The dataset covers actual railway projects of multiple scales and scenarios, and is representative to a certain extent. Therefore, the results have external validity and generalisability. However, real engineering is still affected by policy changes, social environments and unexpected events. The application of models needs to be carefully evaluated and calibrated in combination with the context.

The time complexity of the proposed approach is O(P.G.E), where PPP is population size, G is generations, and E is the cost of one fitness evaluation (CPM propagation over |V| activities and |E|precedence links plus cost/quality aggregation), typically E=O(|V|+|E|). Memory scales as O(P.L) with chromosome length L. On a large rail project (≈2,100 activities, ≈6,000 precedence links, three resource classes), a representative configuration P=200P=200P=200, G=400G=400G=400 yielded ~80,000 fitness evaluations. On a 16-core workstation (3.5 GHz CPU, 64 GB RAM), median wall-clock time was 12.8 minutes with single-threaded evaluation; enabling parallel fitness evaluation across 8–16 workers reduced wall-clock to 3.5–6.1 minutes.For very large instances (≈5,000+ activities), runtime grows near-linearly in practice with|V|+|E|per evaluation; practical mitigation includes (i) parallel evaluation, (ii) elitist population capping, and (iii) warm-starting from the best individuals of previous runs (e.g.when re-optimizing after schedule disturbances). These characteristics make the method suitable for daily or intra-shift replanning on large projects.

5 Discussion

Performance under varied environments. Across urban, suburban, and remote settings and under normal vs. complex geology, IGA consistently outperformed PSO and GA on schedule deviation, cost overrun, and quality compliance. When geology introduced correlated delays and rework risk, PSO/GA frequently converged to locally feasible yet brittle schedules, whereas IGA preserved a portfolio of high-fitness, diverse candidates that adapted after shocks, sustaining lower overruns.

Why IGA performs better (computational reasoning). IGA augments GA's exploration–exploitation balance with immune-based similarity suppression and adaptive operators. The suppression scheme prunes near-duplicates, preserving genotypic diversity and reducing premature convergence. Adaptive p_c, p_m respond to fitness dispersion: when variance narrows, exploration intensifies to escape local basins; when variance widens, exploitation consolidates gains. Empirically, this yields smoother fitness trajectories and faster recovery after constraint or data updates pushed by field telemetry.

Trade-offs. IGA introduces overhead for similarity computation and diversity control. Complexity is $O(P \cdot G \cdot E)$ with an extra similarity term $O(P^2)$ if implemented naively; we mitigate via (i) mini-batch similarity checks, (ii) sparse hashing of chromosomes, and (iii) parallel fitness evaluation. In large instances (≈5k activities), runtimes grow near-linearly with evaluation cost; however, parallelization (8–16 workers) keeps wall-clock within shift-planning windows (minutes).

Practical significance and generalizability. The twin-ready, BIM-linked formulation enables closed-loop replanning, translating optimization outputs into look-ahead simulations and constraint checks, while ingesting progress and inspection data to refresh weights. This supports daily or intra-shift updates without discarding prior high-fitness solutions, improving stakeholder trust and adoption. Given the formulation relies on CPM propagation and measurable quality indices, the approach generalizes to adjacent linear-infrastructure projects with modest adaptation.

Given deployment in public infrastructure, optimization outputs must be auditable and advisory, not fully automated. Mis-specification could affect public safety or budgets; therefore, we expose weight settings, constraint repairs, and change logs, and require human sign-off for schedule changes beyond pre-defined thresholds. For real-time decision support, we outline a BIM/Digital-Twin deployment where optimizer proposals are sandbox-simulated (clash/space, crew paths, resource conflicts) before enactment. Data governance adheres to contractual NDAs and privacy rules; model updates are versioned and stress-tested on disturbance scenarios (geology/weather/supply) prior to rollout.

6 Conclusion

This study focuses on the multi-objective optimization problem in rail construction project management, and deeply analyzes the limitations of traditional management methods and existing intelligent algorithms. By constructing an innovative model integrating multi-objective-IGA, the collaborative optimization of key objectives such as construction period, cost, and quality is achieved. The experimental results show that compared with the traditional critical path method combined with cost budget management mode

(construction period deviation rate 25.0%, cost overrun rate 30.0%, quality compliance rate 70.0%, and comprehensive satisfaction score 4.0 points), as well as particle swarm optimization algorithm (construction period deviation rate 15.2%, cost overrun rate 20.1%, quality compliance rate 80.3%, and comprehensive satisfaction score 6.2 points) and genetic algorithm (construction period deviation rate 18.7%, cost overrun rate 25.3%, quality compliance rate 75.6%, and comprehensive satisfaction score 5.5 points), the fusion multi-objective-IGA method shows excellent performance. In terms of construction period control, the deviation rate is as low as 8.5%, effectively reducing delays; the cost overrun rate is only 12.3%, achieving good cost control; the quality compliance rate is 88.6%, ensuring the quality of the project; the resource utilization rate is 85.4%, improving the efficiency of resource use; the comprehensive satisfaction score is 7.8 points, which is highly recognized. This research result provides a new and effective means for rail construction project management, helps to improve project management efficiency and benefits, promotes the healthy and sustainable development of the industry, and has important guiding and reference significance for future related research and practice.

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3D-DHA-MAFNet: A Multi-View Attention-Enhanced Deep Learning System for Lung Nodule Detection and Classification

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Lung cancer, one of the most lethal malignancies globally, has a high mortality rate, making early screening and accurate diagnosis crucial for improving patient survival rates. Low-dose computed tomography (LDCT) has significantly increased the detection rate of lung nodules, but the vast amount of imaging data poses a significant challenge for manual interpretation. This article proposed a lung nodule computer-aided quantitative diagnostic system based on a three-dimensional convolutional neural network (3D CNN), named 3D-DHA-MAFNet. By integrating deformable convolution network (DCN), hybrid attention mechanism (HAM), and multi-view adaptive fusion network (MAFN), this system significantly enhanced the detection and benign/malignant classification capabilities for small and irregular lung nodules. The model was trained and evaluated on the lung nodule analysis 2016 (LUNA16) and LIDC-IDRI datasets with a patient-level split in the ratio of 7:2:1. The number of training epochs was 200. Data augmentation methods included random rotation (±15°), translation (±5 pixels), and elastic deformation. The performance was compared with baseline models including 3D-UNet, AttentNet, 3DAGNet, 3D multi-scale capsule network (3D-MCN), and 3D multi-view SE CNN (3D MVSECNN). Experiments showed that on the LUNA16 dataset, the model achieved a detection sensitivity of 98.7% with a low false-positive rate of 1.2 per scan, which was a notable improvement over baseline models like 3D-UNet. On the LIDC-IDRI dataset, the classification accuracy for benign and malignant nodules reached 96.8%, with an AUC value of 0.983, and particularly, the sensitivity for malignant nodules was enhanced to 97.5%. Ablation studies verified the synergistic gains of each module, and cross-clinical dataset testing further demonstrated its strong generalization ability. This article presents a high-precision and interpretable intelligent diagnostic tool designed for clinical applications, which holds strong potential to promote the clinical translation of early lung cancer screening.

Povzetek: Članek predstavlja 3D-DHA-MAFNet, globoki učni sistem za zaznavanje in razvrščanje pljučnih nodulov (vozlišč) iz LDCT slik. Z uporabo deformabilnih konvolucij, hibridne pozornosti in večpogledne fuzije dosega visoko točnost, robustnost in dobro posplošljivost na kliničnih podatkih.

1 Introduction

Lung cancer is one of the world's deadliest malignancies. The IARC's *Global Cancer Statistics 2022* shows that there are about 2.5 million new cases and over 1.8 million deaths annually, accounting for 18.7% of all cancer deaths [1]. Early detection and benign/malignant judgment of pulmonary nodules are crucial for improving the five-year survival rate. Low-dose computed tomography (LDCT) screening can significantly increase early detection rates. For example, the NELSON study shows that it can reduce mortality by 24-33% [2]. However, as CT data increases, especially for small, atypical, or nodules with underlying diseases, the reading pressure increases, raising the risk of missed diagnoses and misdiagnoses.

Artificial intelligence (AI), especially computer-aided diagnosis (CAD) systems based on deep learning, has provided new solutions for intelligent pulmonary nodule detection. A three-dimensional convolutional neural network (3D CNN) can extract spatial contextual information from 3D volume images. Compared with 2D networks, it can better capture nodule morphology, density, and spatial distribution features [3]. Previous studies have shown that Li et al. [4] proposed a multi-scale 3D CNN combined with channel and spatial attention to improve small nodule detection rates. Hammad et al. [5] built a lightweight CNN combined with saliency maps, achieving a 99.89% classification accuracy on the LIDC-IDRI dataset.

Nevertheless, lung nodule AI still faces three major challenges. First, small nodules have weak features and blurred boundaries, which are easily confused with blood

vessels, resulting in high missed detection rates [6]. Second, multi-view fusion methods are simple, mostly using static splicing or average weighting, lacking adaptive capabilities [7]. Third, the model's generalization is insufficient. It mostly relies on public datasets and lacks pathological gold standard support, showing unstable performance in real-world clinical settings. Class imbalance also affects model robustness, and Focal Loss or Dice Loss is used to alleviate this issue [8, 9].

To address the aforementioned issues, this study proposed the 3D-DHA-MAFNet system. The deformable convolution network (DCN) was introduced to enhance the adaptability to nodule shape variations, the hybrid attention mechanism (HAM) was used to focus on key areas and reduce false negatives, and the multi-view adaptive fusion network (MAFN) efficiently integrated multi-view information through dynamic weighting. Moreover, the system combined Focal Loss with MixUp/CutMix data augmentation to mitigate class imbalance and improve generalization in complex clinical scenarios. The systematic integration of DCN, HAM, and MAFN enabled the model to maintain high precision while possessing strong generalization ability, providing reliable support for clinical early lung cancer screening. In the future, with the development of multi-center data sharing and privacy protection technologies, the system is expected to achieve broader clinical applications, reduce the burden on physicians, and enhance diagnostic efficiency.

2 Related works

Early detection of lung nodules is critical for improving the survival rates of lung cancer patients. However, traditional 2D CNN suffer from information loss when processing 3D medical image data, limiting their effectiveness in lung nodule detection tasks. To address this, researchers have begun to explore the application of 3D CNN in lung nodule detection. Tan et al. [10] proposed a two-stage lung nodule detection system based on a 3D CNN for detecting candidate nodules and reducing false positives (FP), achieving a detection sensitivity of 97.5% with an average of only one FP per scan on the LIDC-IDRI dataset. Song et al. [11] introduced a 3D CNN and capsule network (CapsNet) model (3D CNN-CapsNet), which achieved a detection rate of 95.19%, sensitivity of 92.31%, specificity of 98.08%, and an F1 score of 0.95 on the early lung cancer program (ELCAP) dataset, notably outperforming other baseline methods. Almahasneh et al. [12] proposed a lung nodule detection model based on a 3D fully convolutional attention mechanism, AttentNet, which demonstrated strong performance in reducing FP on the lung nodule analysis 2016 (LUNA16) dataset, validating the effectiveness of the 3D attention mechanism in lung nodule detection.

Accurate segmentation of lung nodules is critical for subsequent feature extraction and classification tasks. 3D CNN can effectively leverage spatial information from volumetric data, thereby enhancing segmentation accuracy. Xiao et al. [13] proposed the 3D-Res2UNet model, which introduced a Res2Net module on the basis of 3D-UNet to achieve multi-scale feature extraction, thereby enhancing the ability to identify nodule boundaries, and achieved a Dice coefficient of 95.30% and a recall rate of 99.1% on the LUNA16 dataset. Xu et al. [14] designed a 2.5D V-Net combining separable 3D convolution (S3D) with a dual-branch feature fusion module (DFFM), which not only improved the accuracy of lung nodule segmentation but also demonstrated good noise resistance and adaptability to complex anatomical structures. Liu et al. [15] proposed the SCA-VNet model, which combines 3D coordinate attention and edge enhancement mechanisms, achieving a Dice coefficient of 87.50% on the LIDC-IDRI dataset, notably outperforming existing methods and validating the effectiveness of this strategy in lung nodule segmentation. In addition, 3DAGNet achieved efficient detection and localization of lung nodules by combining global search and attention mechanisms with multi-scale feature extraction modules [16].

In the task of classifying the benignity or malignancy of lung nodules, 3D CNN can extract spatial features of nodules to assist doctors in diagnosis. In recent years, a variety of enhanced 3D CNN architectures have been proposed to improve the accuracy and robustness of classification performance. Yang et al. [17] proposed a 3D multi-view SE CNN (3D MVSECNN), which enhanced the modeling ability of features from different views by introducing SE modules. Experimental results on the LIDC-IDRI dataset showed that the model achieved an accuracy of 96.04% and a sensitivity of 98.59% in the binary classification task, and an accuracy of 87.76% in the ternary classification task, all of which were superior to other advanced methods. In addition, Afshar et al. [18] developed a 3D multi-scale capsule network (3D-MCN), which combined the advantages of 3D input, multi-scale feature extraction, and capsule networks. Experiments on the LIDC-IDRI dataset showed that the model achieved an accuracy of 93.12%, a sensitivity of 94.94%, and an AUC of 0.9641, showing strong performance. The improved 3D attention CNN proposed by Huang et al. [19] combines feature fusion and hybrid loss functions, enhancing the interaction of different channel and spatial features in the task of lung nodule classification, thereby improving the classification ability of small and ill-defined nodules. On the NLST dataset, the model achieved an accuracy of 85.3% and an AUC of 0.9042, validating the effectiveness of attention mechanisms and hybrid loss functions in improving the model's discriminative ability. This echoes the idea adopted in this article's method of using the HAM module, both emphasizing the enhancement of key feature areas through attention to improve the recognition performance of indistinct nodules. The V-3DResNets model proposed by Prithvika and Anbarasi [20], based on residual network variants and slice grouping design, improves the accuracy of nodule localization and detection in lung nodule detection through multi-scale feature extraction and slice-aware mechanisms. This method emphasizes the full utilization

of inter-slice information in volumetric data, which helps to improve the detection rate of small nodules. This strategy is similar to the goal of this article's MAFN module in multi-view feature fusion, both aiming to dynamically integrate spatial information to enhance the perception of nodule heterogeneity and small-sized nodules.

In summary, in recent years, based on 3D CNN, researchers have significantly improved the performance of lung nodule CAD systems by introducing methods such as multi-view, attention mechanisms, multi-scale feature fusion, improved loss functions, and false-positive reduction strategies (Table 1). However, further research is required to enhance the generalization capability of these models, reduce their computational complexity, and improve their interpretability and reliability in clinical settings.

Table 1: Summary of relevant work on lung nodule detection and classification using 3D deep learning methods

References	Datasets	Key Metrics (Accuracy/Sensitivity/AUC)	Main Structural Innovations	Limitations
Tan et al. [10]	LIDC-IDRI	Sensitivity: 97.5%, FP: 1 per scan	Two-stage 3D CNN for detection and FP reduction	Limited generalization ability for small nodules
Song et al. [11]	ELCAP	Accuracy: 95.19%, Sensitivity: 92.31%	3D CNN + CapsNet	High computational cost
Almahasneh et al. [12]	LUNA16	–	AttentNet: 3D fully convolutional network with attention	Classification results not reported
Xiao et al. [13]	LUNA16	Dice coefficient: 95.30%, Recall: 99.1%	3D-Res2UNet with multi-scale feature extraction	Focused solely on segmentation tasks
Xu et al. [14]	LIDC-IDRI	–	2.5D V-Net with S3D and DFFM	Limited to segmentation tasks
Liu et al. [15]	LIDC-IDRI	Dice coefficient: 87.50%	SCA-VNet with 3D coordinate attention and edge enhancement mechanism	Low Dice coefficient for complex nodules
Yang et al. [17]	LIDC-IDRI	Accuracy: 96.04%, Sensitivity: 98.59%	3D MVSECNN with SE module	Limited multi-view adaptive fusion capability
Afshar et al. [18]	LIDC-IDRI	Accuracy: 93.12%, AUC: 0.9641	3D-MCN	High model complexity
Huang et al. [19]	NLST	Accuracy: 85.3%, AUC: 0.9042	An improved 3D attention CNN that combines feature fusion and hybrid loss functions	Lower performance on public datasets

3 System design and methods

To enhance the detection capability of small, edge-blurred, or irregularly shaped lung nodules in LDCT images, this article proposed a 3D CNN system integrating DCN, HAM, and MAFN (3D-DHA-MAFNet) (Figure 1). The system comprised three core modules: Feature extraction module: Combining DCN with HAM to improve the representation ability of small nodules with complex shapes; MAFN: Dynamically weighting multi-directional features through an SE module to achieve information integration; Optimization module: Introducing Focal Loss to address class imbalance and supplements with MixUp/CutMix data augmentation to alleviate the scarcity of 3D imaging samples.

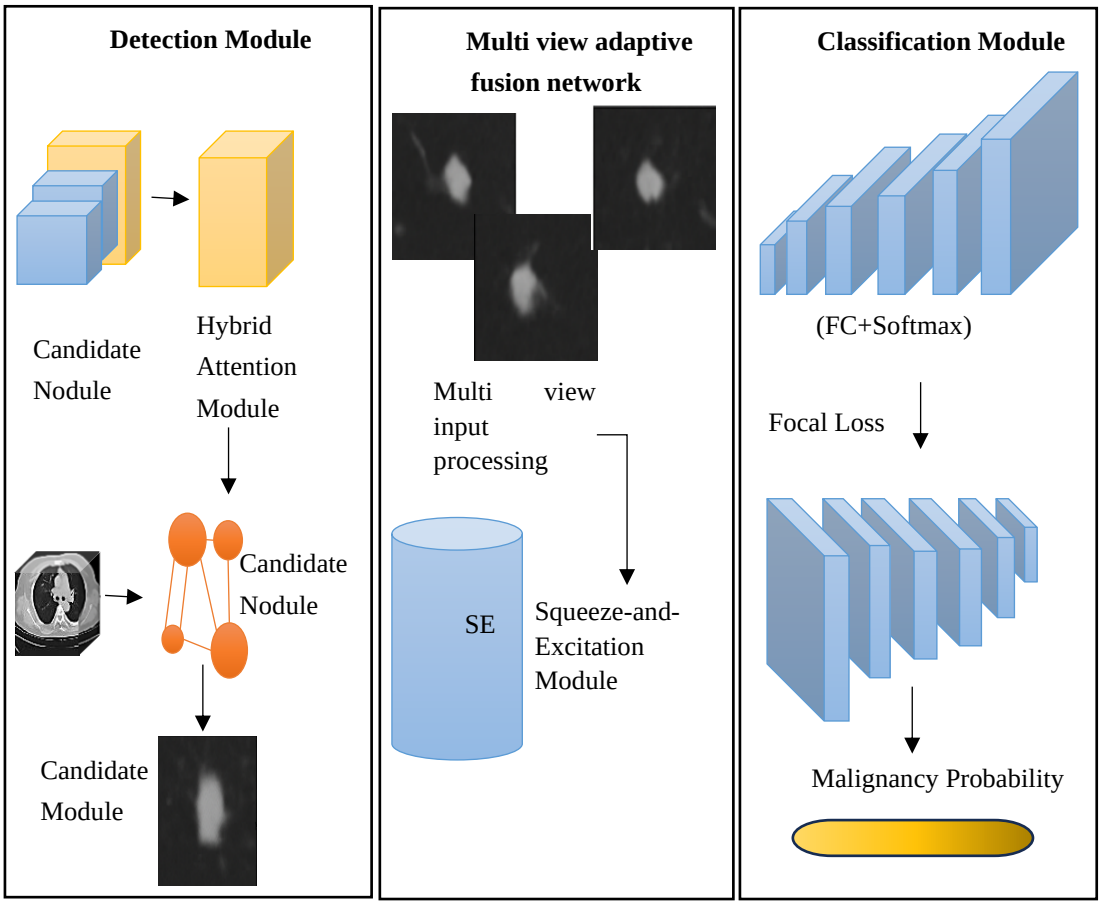


Figure 1: Schematic diagram of the three major modules of 3D-DHA-MAFNet

3.1 DCN and HAM feature extraction module

To enhance the detection ability of small-sized and irregular-shaped nodules (such as ground-glass nodules), DCN and HAM were introduced into the Backbone in this study. The Backbone is composed of four layers of 3D convolution, with parameters for each layer as follows: Conv1 (3×3×3, stride 1, channels 32, ReLU + BatchNorm3D), Conv2 (3×3×3, stride 2, channels 64), Conv3 (3×3×3, stride 2, channels 128), Conv4 (3×3×3, stride 2, channels 256). DCN is embedded between Conv2 and Conv3 to dynamically capture nodule edges in mid-level features; HAM is embedded behind Conv4 to enhance attention to key areas in high-level semantic features.

DCN: The standard 3D convolution operates on the input feature map x at the fixed sampling points $\{d_l\}_{l=1}^{L}$, and its output is as follows.

$$y(d_0) = \sum_{l=1}^{L} w_l \cdot (xd_0 + xd_l) \quad (1)$$

d_0 denotes the position coordinates on the output feature map; $d_l \in Z^3$ represents the convolution kernel sampling offsets; w_l represents the convolutional kernel parameters. The irregular structure of nodule edges means that fixed sampling limits the ability to model non-Euclidean structures. DCN achieves dynamic sampling by learning offsets $\Delta d_l \in R^3$.

$$y(d_0) = \sum_{l=1}^{L} w_l \cdot (xd_0 + xd_l + x\Delta d_l) \quad (2)$$

This mechanism endows the receptive field with the ability of nonlinear deformation, enhancing the ability to capture morphological features such as nodule edges, protrusions, or cavities.

HAM: The HAM module enhances features by combining channel attention and spatial attention. The channel attention (SE) globally weights each channel.

$$Z_C = GAP(x_c) = \frac{1}{V}\sum_{v=1}^{V} x_c\,(v) \quad (3)$$

$$S_C = \sigma(W_2 \cdot ReLU(W_1 \cdot Z_c)) \quad (4)$$

$$X_c^{att} = S_C \odot X_c \quad (5)$$

Spatial attention further highlights significant regions by performing max pooling and average pooling across the channel dimension, concatenating the results, and then generating the attention map MSM_SMS through a 3×3×3 convolution.

$$F_{avg} = \frac{1}{C}\sum_{c=1}^{C} F_c, F_{max} = max_c F_c \quad (6)$$

$$M_S = \sigma(Conv_{3\times3\times3}([F_{avg} \oplus F_{max}])) \quad (7)$$

$$F^{out} = F^{in} \otimes M_s \quad (8)$$

F_{avg} denotes the result of average pooling on the channel dimension, and F_{max} denotes the result of maximum pooling on the channel dimension, with dimensions $[D,H,W]$; C represents the number of channels in the feature map; Conv3×3×3 indicates a 3D convolution operation with a kernel size of 3×3×3 and an output channel count of 1, used to generate the spatial attention map M_s; F^{in} represents the feature map weighted by channel attention (output of the SE module); F^{out} represents the output feature map weighted by both

spatial and channel attention, which is the final output of this module. The HAM helps enhance the model's response to small nodules and blurry areas, improving localization accuracy and edge discrimination.

3.2 MAFN

Lung nodules display considerable morphological variations across different anatomical planes (axial, coronal, and sagittal). Relying exclusively on a single viewing plane may lead to the omission of critical structural information. To fully exploit the redundant and complementary features in multi-view images, this article designed a MAFN based on three-view input and SE-guided fusion mechanism. This structure comprised three key components: view slicing generation, multi-view feature extraction, and attention-guided fusion.

3.2.1 Multi-view input processing

It is assumed that the original lung nodule cubic input be a tensor.

$$x \in \mathbb{R}^{D\times H\times W} \tag{9}$$

D, *H*, *W* represent the depth (number of axial slices), height, and width of the cube, respectively. To achieve multi-view modeling, 2D slice sequences in three anatomical directions are extracted from this tensor.

Axial slices are directly extracted along the axial direction to form the original input sequence.

$$x_A = x \in \mathbb{R}^{D\times H\times W} \tag{10}$$

The dimensions of the original tensor are rearranged to obtain sagittal view slices.

$$x_s = permute(x, [2,0,1]) \in \mathbb{R}^{D\times H\times W} \tag{11}$$

Similarly, the coronal view is obtained through transposition.

$$x_C = permute(x, [1,2,0]) \in \mathbb{R}^{D\times H\times W} \tag{12}$$

The inputs from the three directions are fed into a structurally shared CNN for feature extraction, resulting in feature vectors for each view.

$$F_A = F_{CNN}(x_A), F_S = F_{CNN}(x_S), F_C = F_{CNN}(x_C) \tag{13}$$

$F_{\mathrm{CNN}}(\cdot)$ represents the feature extraction network with shared parameters, which is used to maintain structural consistency and reduce model redundancy.

All views are cropped to a 32×32×32 voxel region centered on the nodule and undergo rotation normalization (alignment of the axial, coronal, and sagittal planes with the scanning coordinate system) to ensure multi-view spatial consistency.

3.2.2 SE-guided fusion mechanism

Direct concatenation of multi-view features may introduce a large amount of redundant or irrelevant information. To enhance the discriminative ability of feature fusion, this article introduced the SE module, which assigned importance weights to each view through a dynamic weighting mechanism.

It is assumed that any view feature is $f_i \in \mathbb{R}^c$, where $i \in${A,S,C} represents the view index, the α_i for this view is first calculated through an SE attention branch.

$$\alpha_i = \sigma(W_2 \cdot \delta(W_1 \cdot f_i) \tag{14}$$

After calculating the attention weights α_A, α_S, α_C for the three views, the features are fused in a weighted manner to obtain a unified multi-view representation.

$$\mathrm{f}_{fusion} = \alpha_A \cdot \mathrm{f}_A + \alpha_S \cdot \mathrm{f}_S + \alpha_C \cdot \mathrm{f}_C \tag{15}$$

In multi-view feature fusion, although direct concatenation followed by convolution or fully connected layers is commonly used, it increases the feature dimension, leading to redundancy and computational overhead. The SE-based weighted sum method is more parameter-efficient, allowing dynamic adjustment of the importance of each view, reducing redundancy, improving training stability, and intuitively reflecting the contribution of each view, thereby enhancing interpretability. In multi-view or multi-modal image analysis, this method achieves better inference efficiency while maintaining performance [21, 22]. Therefore, this study adopted this strategy to balance performance, efficiency, and interpretability.

3.3 Classification optimization and training strategies

To effectively enhance the robustness and generalization ability of the model in classifying the benignity or malignancy of lung nodules, this article designed two key training optimization strategies: First, Focal Loss was introduced to address the class imbalance issue caused by the relatively small proportion of malignant nodule samples; second, MixUp and CutMix data augmentation techniques were jointly used to effectively increase the diversity of training samples in 3D medical imaging.

3.3.1 Focal loss

Because benign nodule samples far outnumber malignant ones, traditional cross-entropy loss is easily dominated by the majority class, resulting in insufficient model recognition ability for malignant nodules. To focus on hard-to-classify samples and reduce the risk of false negatives, this study combined Focal Loss with cross-entropy loss at a weight ratio of 0.75:0.25, where Focal Loss targeted difficult samples and cross-entropy ensured overall training stability.

The expression for Focal Loss is as follows.

$$\zeta_{focal} = -\alpha_t(1-\hat{y}_t)^2 \log(\hat{y}_t) \tag{16}$$

$\hat{y}_t \in [0,1]$ means the model's predicted probability for the true class. The class balance factor, $\alpha_t \in [0,1]$, is used to increase the weight of minority classes (such as malignant nodules). The focusing parameter, 2, is used to adjust the penalty for easily classified samples and is set to 2 in this article. When $\hat{y}_t$ approaches 1, that is, when the sample is easily correctly classified, the loss value will be substantially compressed. Conversely, when $\hat{y}_t$ is small (indicating that the model is not confident in its prediction for the sample), the loss function will assign a higher penalty, causing the model to focus more on difficult samples. Through this mechanism, Focal Loss substantially improves the model's sensitivity to minority classes such as malignant nodules and effectively reduces the FN rate (FNR).

3.3.2 Mixed augmentation strategy (MixUp + CutMix)

Medical images, especially LDCT lung nodule data, face the problem of limited sample size, and the training of 3D models requires an even larger sample scale. To address this, MixUp and CutMix, two mixed augmentation strategies, were incorporated to improve the diversity of sample distributions and enhance boundary robustness from the perspectives of global feature synthesis and local region perturbation, respectively.

MixUp is a global linear interpolation augmentation method. It generates new training samples by linearly mixing two samples and their corresponding labels.

$$\widetilde{\boldsymbol{X}} = \lambda \boldsymbol{X}_i + (1-\lambda)\boldsymbol{X}_j, \widetilde{\boldsymbol{Y}} = \lambda \boldsymbol{Y}_i + (1-\lambda)\boldsymbol{Y}_j \quad (17)$$

X_i, X_j mean the volume images of two input samples. Y_i and Y_j represent their corresponding labels (encoded using one-hot encoding). $\lambda \sim \text{Beta}(\alpha,\alpha)$ represents the mixing weight, with α typically ranging from 0.2 to 0.4.

This strategy achieves continuous modeling in both the image space and the label space, enhancing the model's ability to represent the transition regions of class boundaries and reducing the risk of overfitting.

CutMix is a local masking augmentation method. It forms new training samples by randomly cutting out a cuboid region from one image and replacing it with the same location region from another image.

$$\widetilde{\boldsymbol{X}} = \boldsymbol{M} \circledast \boldsymbol{X}_i + (\boldsymbol{1}-\boldsymbol{M}) \circledast \boldsymbol{X}_j, \widetilde{\boldsymbol{Y}} = \lambda \boldsymbol{Y}_i + (1-\lambda)\boldsymbol{Y}_j \quad (18)$$

$M \in \{0,1\}^{D\times H\times W}$ means a randomly generated binary cuboid mask, indicating the region to be replaced. $\odot$ denotes element-wise multiplication. $\lambda = \frac{\sum M}{D \cdot H \cdot W}$ represents the proportion of the retained region and is also used to calculate the weight of the new label. By locally replacing regions, CutMix disturbs the model's regional focus, effectively enhancing the model's robustness to image structural uncertainty and preventing it from "memorizing" the training set based on local features.

During the training process, the switching between MixUp and CutMix was done randomly on a batch-wise basis, meaning that each mini-batch randomly decided whether to use MixUp or CutMix with a fixed probability of 0.5 to achieve the complementarity of the two strategies. MixUp provides overall smooth feature transitions, while CutMix introduces local perturbations to challenge the model's discriminative boundary capabilities. Together, they effectively improve the model's generalization ability and alleviate overfitting caused by limited data.

3.4 Model training and inference process

In Figure 2, the training process first cropped and normalized the lung nodule region from LDCT images into a fixed-size 3D cube, then generated three sets of 2D slices along the three orthogonal axes as input to a 3D CNN with the same structure. The network introduced DCN to enhance spatial modeling ability, embeded HAM to capture local and global features, and integrated multi-view features through the SE mechanism during the fusion stage, finally outputting the probability of nodule malignancy through a fully connected layer. During training, Focal Loss addressed class imbalance, combined with MixUp and CutMix to enhance sample diversity, achieving end-to-end optimization. The parameter settings were as follows: Focal Loss α_t=0.75, γ=2; Cosine Annealing learning rate with an initial value of 0.001 and T_max=200; MixUp and CutMix were randomly switched with a probability of 0.5, with α values of 0.3 and 1.0, respectively.

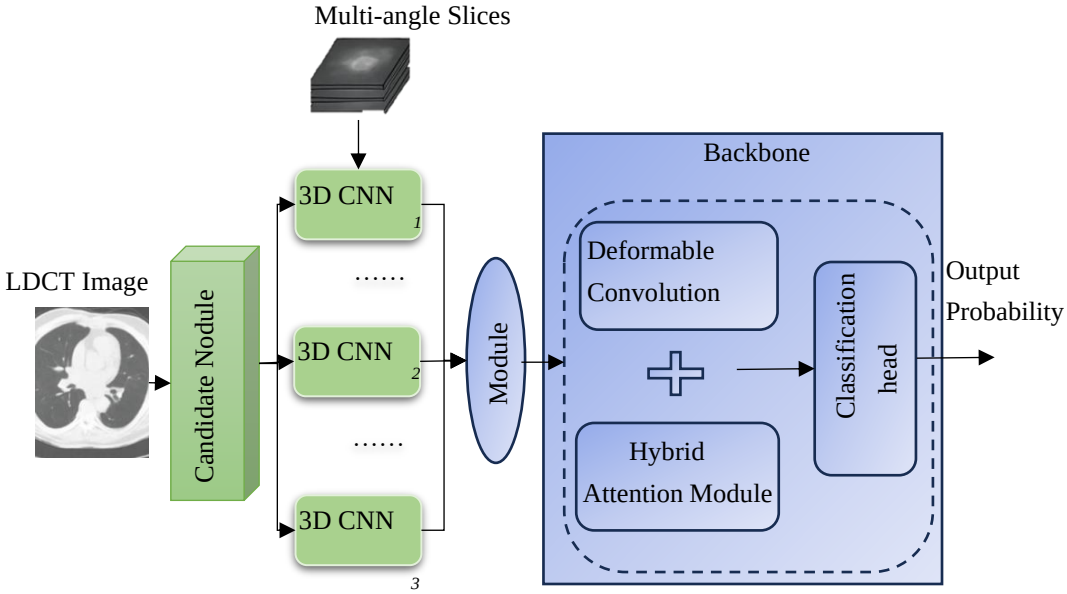


Figure 2: Model training and inference flowchart

4 Experiments and results analysis

To verify the effectiveness of 3D-DHA-MAFNet in lung nodule detection and classification, experiments were conducted on the LIDC-IDRI and LUNA16 datasets and comparisons were performed with 3D-UNet, AttentNet, 3DAGNet, 3D-MCN, 3D-MVSECNN, 3D-ResAttNet, and 3D ViT-CNN. The experiments were carried out on an NVIDIA A100 GPU, using PyTorch and the Adam optimizer, with an initial learning rate of 0.001, a batch size of 8 and 200 training epochs. Data augmentation included random rotation (±15°), translation (±5 pixels), and elastic deformation. The network's Backbone was a 3D-ResNet18 with four residual blocks, using 3×3×3 convolutional kernels with 64/128/256/512 channels, followed by BatchNorm and ReLU after convolution.

4.1 Experimental datasets and evaluation metrics

The effectiveness and robustness of 3D-DHA-MAFNet were verified in this study using two authoritative public lung nodule datasets. The LIDC-IDRI dataset, released by the NLST, contains 1,018 LDCT scans with a total of 2,636 nodules, of which 1,423 are benign and 1,213 are malignant. Each nodule is provided with its center location, boundary contour, and a malignancy likelihood score based on a 5-point scale. In this article, nodules with an average score ≤3 are defined as benign, and those with a score ≥4 are defined as malignant. Nodules with a standard deviation of the score greater than 1.2 (about 8%) are excluded. The LUNA16 dataset is derived from LIDC-IDRI. After removing nodules without annotations or with a diameter of less than 3 mm, it included 888 scans and 1,186 valid nodules, which were used for standard evaluation of automatic detection tasks. The data were divided into training, validation, and test sets at a ratio of 7:2:1 at the patient level to ensure no overlap, thereby guaranteeing the independence and generalizability of the evaluation. All results were based on stratified 5-fold cross-validation and reported as mean ± standard deviation. Hyperparameters were only optimized on the validation set without using nested cross-validation.

The evaluation metrics for the detection task included sensitivity, FP per scan (FP/Scan), and Dice coefficient.

Sensitivity is used to measure the model's ability to identify all true nodules.

$$Sensitivity = \frac{TP}{TP+FN} \tag{19}$$

True positives (TP) refer to the number of true nodules that are correctly detected. FN: the number of true nodules that are missed by the detection model.

FP/Scan indicates the number of false detections per CT scan, reflecting the model's false alarm rate. The calculation method is as follows.

$$FP/Scan = \frac{False\ Positives}{Number\ of\ Scans} \tag{20}$$

The Dice coefficient is a measure of the overlap between the predicted nodule region by the model and the actual nodule annotation.

$$Dice = \frac{2\times|P\cap G|}{|P|+|G|} \tag{21}$$

P and *G* are the voxel sets of the predicted and true nodules, respectively.

For the classification task, the model is evaluated using accuracy, area under the ROC curve (AUC), sensitivity, specificity, and F1-score.

Accuracy reflects the proportion of overall correct classifications made by the model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{22}$$

TN represents the number of truly benign samples that are correctly identified as benign, while *FP* represents the number of benign samples that are falsely identified as malignant.

AUC is used to measure the model's ability to distinguish between benign and malignant nodules. The closer the AUC is to 1, the better the classification performance.

Recall rate and specificity are employed to evaluate the model's capability in detecting malignant and benign nodules, respectively. A high recall rate reflects the model's strong performance in identifying malignant nodules and a correspondingly low risk of FN. A high specificity indicates that the model can effectively avoid misdiagnosing benign nodules as malignant, reducing the burden of FP. Recall rate is calculated in the same way as sensitivity, and the equation for calculating specificity is as follows.

$$Specificity = \frac{TN}{TN+FP} \tag{23}$$

The F1-score is a harmonic mean metric used in the evaluation of classification model performance.

$$F1-score = 2\times\frac{Precision\times Recall}{Precision+Recall} \tag{24}$$

To quantify the statistical significance of performance differences among different models, this study employed the two-tailed paired *t*-test for hypothesis testing. Specifically, the performance metrics (such as accuracy, sensitivity, AUC) obtained from each fold of the five-fold cross-validation were regarded as paired sample points. The mean differences between 3D-DHA-MAFNet and each baseline model at these sample points were compared. The null hypothesis (H_0) was that there was no significant difference in performance between the two models. If the calculated *P*-value was less than the significance level α (set at 0.05), the null hypothesis was rejected, and the performance difference was considered statistically significant.

4.2 Performance comparison of the detection module

To verify the effectiveness of the proposed 3D-DHA-MAFNet model in lung nodule detection, comparative experiments were conducted with the classic 3D-UNet, AttentNet, and 3DAGNet, and the results are shown in Figure 3. On the public LUNA16 dataset, the 3D-DHA-MAFNet achieved notably better performance in the lung nodule detection task than existing models.

Compared with advanced models such as 3D-UNet, AttentNet, and 3DAGNet, its overall sensitivity was increased to 98.7%, and the FP rate was controlled at 1.2 per scan, with improvements of 5.6% and 2.3 per scan, respectively, demonstrating higher detection ability and stronger false alarm suppression effect. In the detection of small nodules with a diameter of less than 5 mm, the sensitivity was increased to 95.2%, which was 8.1% higher than that of 3D-UNet (P<0.001), indicating the model's advantage in high-difficulty recognition tasks. The performance improvement can be primarily attributed to the incorporation of the DCN and HAM modules, which strengthened the adaptive receptive field construction for capturing nodule shape edges and enhanced the focus on low-contrast regions, respectively. Finally, the Dice coefficient was increased to 94.5%, reflecting the model's strong performance in nodule localization and segmentation accuracy.

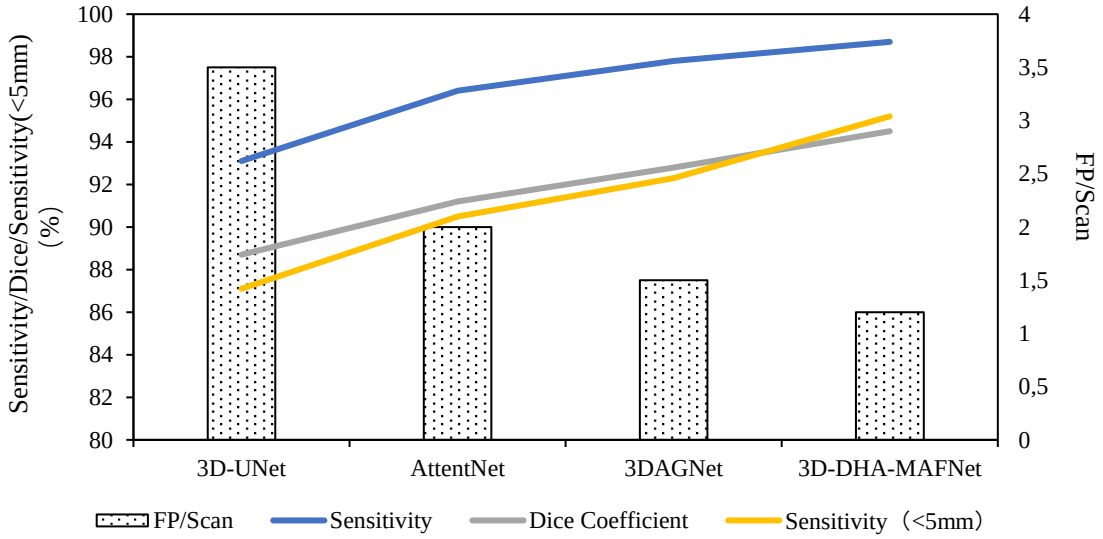


Figure 3: Performance comparison of lung nodule detection (LUNA16 dataset)

4.3 Performance analysis of benign and malignant nodule classification

In the task of lung nodule malignancy classification, 3D-DHA-MAFNet outperformed 3D-MCN and 3D-MVSECNN on the LIDC-IDRI dataset (Figure 4). Under five-fold cross-validation, the average classification accuracy reached 96.8%, with an AUC of 0.983, higher than that of 3D-MVSECNN (accuracy 96.0%, AUC 0.975). The F1 score for malignant nodule identification was 0.971, with sensitivity and specificity of 97.5% and 96.1% respectively, showing significant differences compared with baseline models (P<0.01). The performance improvement was mainly due to Focal Loss mitigating class imbalance, which increased the sensitivity for malignant nodules from 93.8% to 97.5%, and the MAFN module dynamically fusing multi-view information to enhance the recognition ability of heterogeneous structural features, thereby increasing the classification accuracy by 3.6% compared with single-view models.

To evaluate the robustness of the model in real-world clinical settings, a multi-type interference test set was constructed, including motion artifacts (σ=1.5), Gaussian noise (variance 0.01), low-dose artifacts, and tiny nodules (diameter <3 mm). On this test set, the classification accuracy of 3D-DHA-MAFNet still reached 95.4%, with a sensitivity of 93.7% for tiny nodules, significantly higher than that of 3D-MVSECNN (92.1%) and 3D-MCN (91.8%), and with an AUC>0.94 in images containing noise and motion artifacts, demonstrating strong robustness, which was attributed to the MixUp and CutMix augmentation strategies.

In summary, 3D-DHA-MAFNet still performed stably in heterogeneous data environments, with strong clinical practicability and potential for promotion.

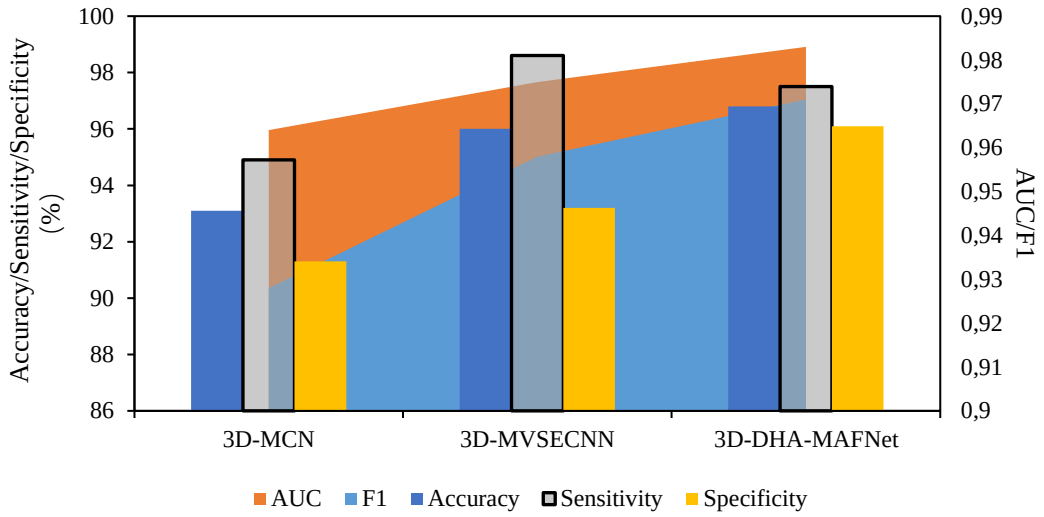


Figure 4: Performance comparison of benign and malignant classification

4.4 Comparison of efficiency and interpretability with the latest 3D CNN/transformer models

To evaluate the practical application value of 3D-DHA-MAFNet, this study compared it with 3D-ResAttNet and 3D ViT-CNN in terms of computational efficiency, model complexity, and interpretability (Figure 5, Figure 6). Experiments on an NVIDIA A100 GPU showed that 3D-DHA-MAFNet had 28.5M parameters, lower than ViT-CNN (45.2M) and slightly higher than 3D-ResAttNet (25.8M); each training epoch took about 12 minutes, and inference was 0.28 seconds per scan, meeting the near real-time clinical needs. In terms of interpretability, the saliency maps generated by the HAM module combined with the multi-view fusion of MAFN can intuitively display the nodule regions the model focused on, and assist doctors in understanding the decision-making process with Grad-CAM. In comparison, 3D-ResAttNet provided local attention but lacked multi-view integration; ViT-CNN captured global information but had difficulty in precisely locating small nodules. In summary, 3D-DHA-MAFNet achieved high performance while maintaining low computational cost and strong clinical interpretability.

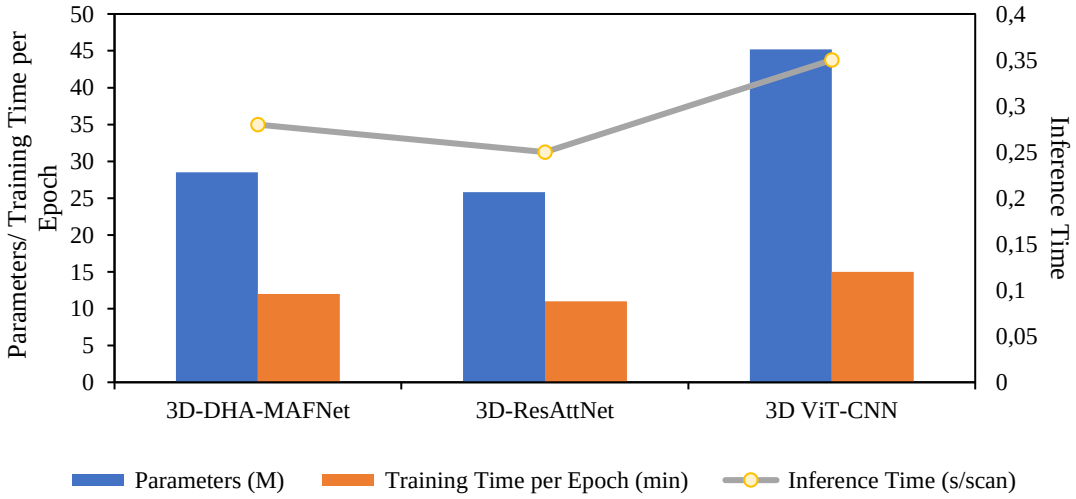


Figure 5: Comparison of computational efficiency and model complexity with the latest 3D CNN/Transformer models

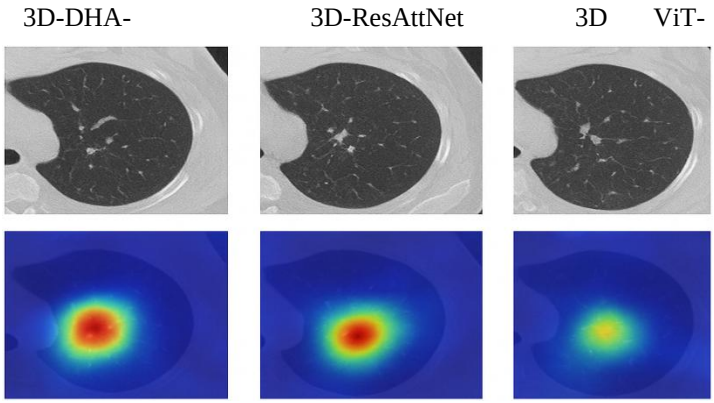


Figure 6: Comparison of Grad-CAM visualization for 3D-DHA-MAFNet, 3D-ResAttNet, and ViT-CNN (Red hotspots: Areas of high attention)

4.5 Ablation study

To verify the contributions of each module to the model's performance, systematic ablation experiments were designed (Figure 7). The results showed that after the DCN module was removed, the sensitivity of small nodule detection decreased by 4.2%, and the Dice coefficient decreased by 3.2%, indicating that DCN is crucial for capturing nodule shape variations. Removing the HAM module resulted in a 3.1% decrease in the Dice coefficient (P<0.05) and a significant decline in overall classification performance, indicating its central role in enhancing the discriminability of local features. Moreover, disabling the MAFN reduced the classification accuracy from 96.8% to 94.1%, highlighting the importance of multi-view synergy in representation learning. Even in terms of data augmentation strategies, jointly canceling MixUp and CutMix would cause the F1 value to drop to 0.949, emphasizing the positive impact of multi-strategy integration on model robustness. Overall, there was a clear synergistic gain among the modules, and the combination of the three can substantially enhance the model's perception and classification capabilities for complex and irregular nodules.

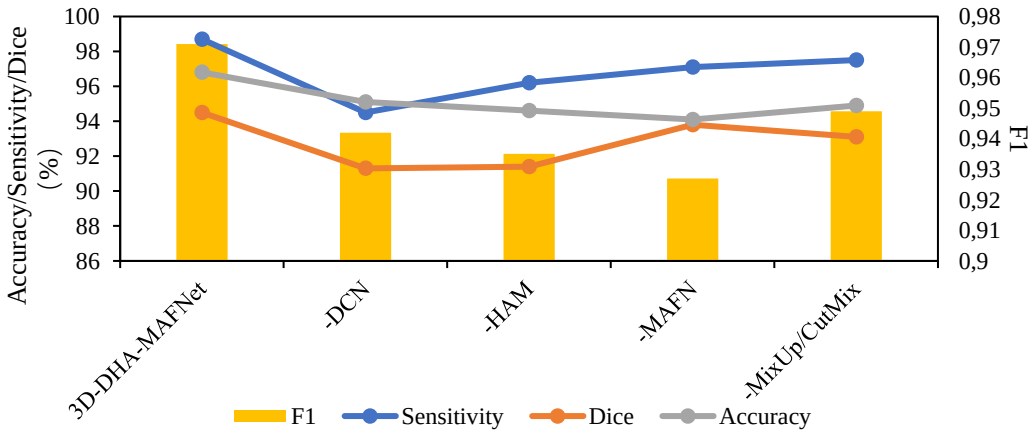


Figure 7: Comparison of module ablation experiment results

4.6 Cross-dataset generalization ability test (internal clinical data)

To verify the generalization ability of 3D-DHA-MAFNet, this study selected a clinical CT dataset of 200 cases confirmed by pathology (92 malignant and 108 benign nodules, with diameters ranging from 3 to 28 mm, scanned by Philips with slice thickness of 1.0-2.5 mm, 120 kVp, 100-250 mAs), which had undergone anonymization. All nodules were annotated by experienced radiologists, with pathological biopsy results serving as the gold standard. The model performed excellently on this dataset (Figure 8, Figure 9), with a sensitivity of 96.2%, accuracy of 94.7%, and AUC of 0.962, significantly outperforming 3D-MVSECNN, 3DAGNet, AttentNet, 3D-UNet, D-ResAttNet, and ViT-CNN (P<0.05). Although the performance was slightly lower than that on the LIDC-IDRI test set (due to the influence of scanning standards and artifacts), 3D-DHA-MAFNet had the smallest drop, demonstrating strong cross-source transferability and clinical applicability.

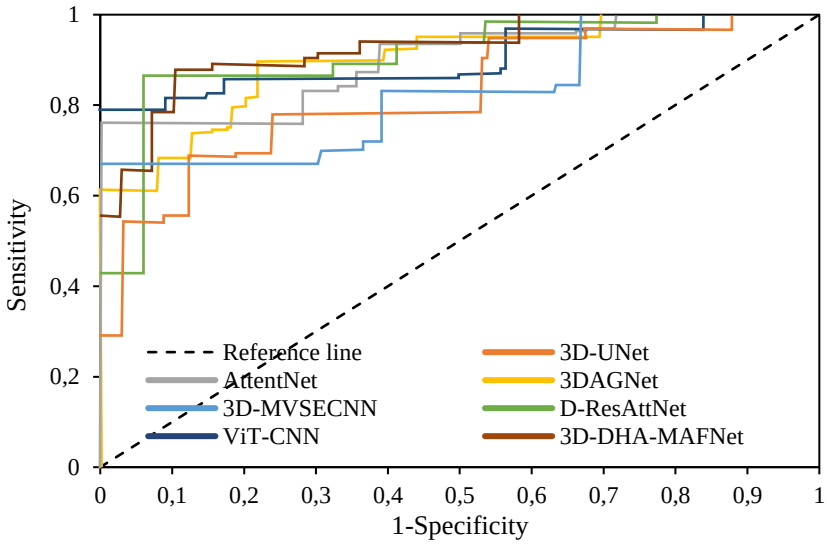


Figure 8: Classification ROC curves of different models

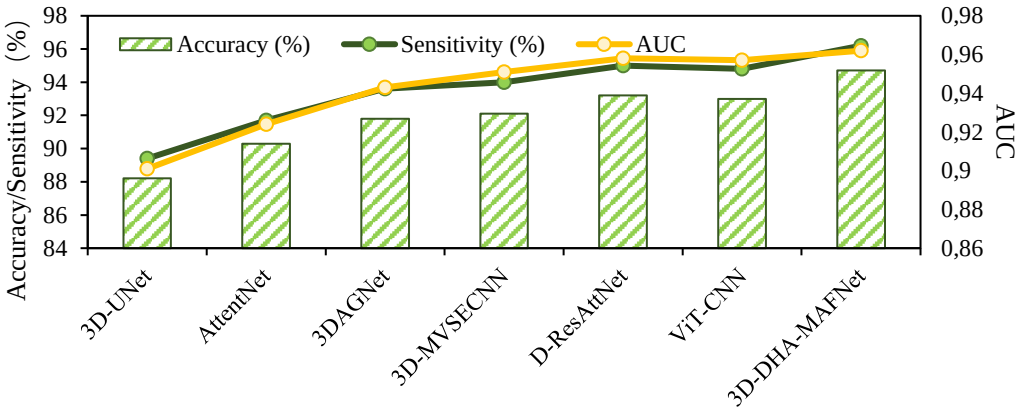


Figure 9: Performance comparison of different models across datasets (internal clinical dataset)

On the internal dataset, the sensitivity of 3D-UNet was only 89.4%, AttentNet and 3DAGNet decreased by about 3-5%, D-ResAttNet was 95.0%, and ViT-CNN had a sensitivity of 94.8% and an AUC of 0.957. In contrast, 3D-DHA-MAFNet, relying on the MAFN and HAM modules, maintained high robustness in the identification of small nodules and in heterogeneous lesion scenarios, showing the best performance and significant potential for clinical application.

4.7 Robustness analysis in heterogeneous data environments

To verify the stability of 3D-DHA-MAFNet in a multi-center clinical setting, this study collected CT data from 150 cases confirmed by pathology from three hospitals (GE, Siemens, Philips) (68 malignant and 82 benign cases, with slice thickness of 1.0-2.5 mm, 120 kVp, 100-250 mAs). On this heterogeneous dataset, the model achieved a classification accuracy of 94.2%, an AUC of 0.958, a sensitivity of 95.6%, and a specificity of 92.9%, all of which were significantly better than the comparison models. For different manufacturers' equipment and scanning protocols, the model's performance remained stable; on samples containing motion artifacts and noise, the accuracy was still >93%, demonstrating good device-independence, protocol-adaptability, and clinical robustness, providing reliable support for practical applications (Figure 10).

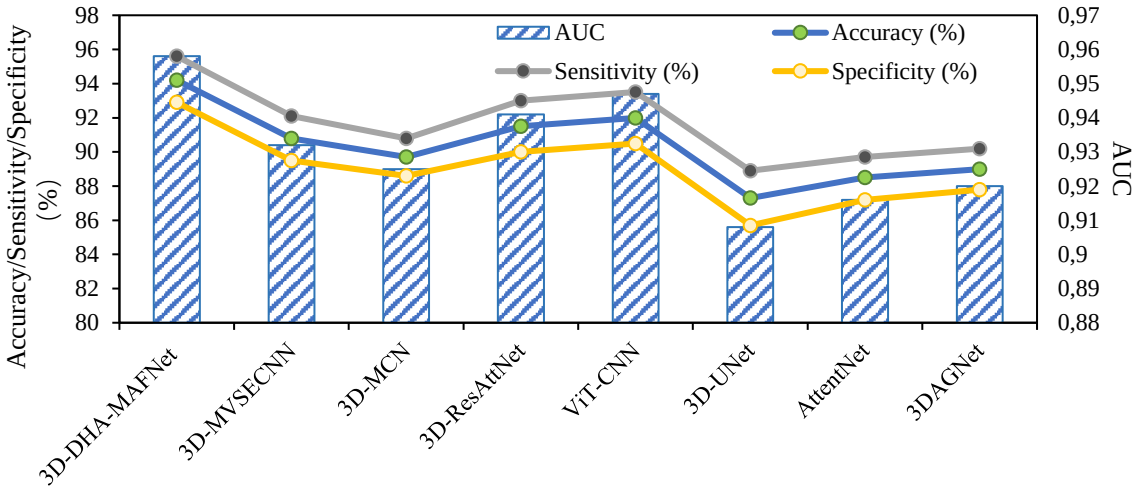


Figure 10: Comparison of benign-malignant classification performance of different models on multi-center heterogeneous clinical datasets

5 Discussion

The 3D-DHA-MAFNet system, integrating DCN, HAM, and MAFN, was proposed in this study. Experiments on public and internal clinical data have shown that the system performed excellently in the tasks of lung nodule detection and benign-malignant classification. Quantitative results indicated that in the LUNA16 detection task, the model had a detection sensitivity of 98.7%, with only 1.2 FP per scan, and a sensitivity of 95.2% for small nodules (<5 mm), significantly reducing the risk of missing early lesions. Its performance surpassed that of the classic 3D-UNet and recent advanced models such as AttentNet [12] and 3DAGNet [16]. In the LIDC-IDRI classification task, the accuracy was 96.8%, the AUC was 0.983, and the sensitivity for malignant nodules was as high as 97.5%, outperforming 3D-MVSECNN [17] and 3D-MCN [18]. Compared with the multi-scale feature pyramid of Li et al. [4] and the 3D multi-scale CNN of Peng et al. [6], this study enhanced feature representation through the synergy of DCN and HAM, and further improved the identification performance of malignant nodules by combining Focal Loss, MixUp, and CutMix strategies.

In terms of qualitative and interpretability aspects, the HAM module combined with Grad-CAM can generate clear attention heatmaps that highlight small and ill-defined nodules. The MAFN module demonstrates the contribution of different views to the decision-making through dynamic weights (αA, αS, αC) [17], enhancing model transparency and providing auxiliary references for clinical use. The performance improvement is mainly attributed to three aspects: the deep integration of DCN and HAM captures irregular shapes and key information; MAFN adaptively fuses multi-view features to enhance adaptability to nodule shape variations; optimized training strategies improve generalization and robustness. In addition, recent studies have shown that multi-layer optimization and multi-modal fusion can further enhance model robustness and cross-center adaptability. For example, RREASO algorithm by Li e al. [23] and the VEnDR-Net model [24] provide referable strategies for multi-model fusion and feature integration.

Despite the encouraging results, this study still has limitations. The scale of the training data is limited, with an insufficient number of pathologically confirmed malignant nodules (n=92), and the performance on non-public clinical data has declined (accuracy dropped from 96.8% to 94.7%), reflecting the challenge of generalization posed by different medical center equipment and scanning protocols. Although the introduction of DCN, HAM, and MAFN modules has improved performance, it has increased the number of parameters and computational complexity. Although the inference speed is 0.28 seconds per scan, optimization is still needed in resource-constrained environments. In the future, larger-scale, multi-institutional, and class-balanced datasets should be used to enhance generalizability. All clinical data were strictly anonymized, and the research protocol was approved by the IRB. The clinical application of AI-assisted diagnosis needs continuous attention to transparency, fairness, and validation in diverse populations to ensure safety and reliability.

From the perspective of translating research into clinical practice, 3D-DHA-MAFNet still needs to address challenges in many aspects, including multi-center validation to assess robustness, integration with existing workflows (such as PACS systems), regulatory approval, and standardized evaluation, enhancing clinically understandable interpretability, and data privacy and security protection. In the future, adaptive and robust control methods in complex dynamic systems, such as adaptive fuzzy control, output-feedback synchronization, and robust neural adaptive control [25-29], can be used for reference to dynamically adjust model parameters in the presence of noise interference, cross-center differences, or insufficient data, thereby enhancing the stability, generalizability, and clinical credibility of CAD systems.

6 Conclusion

To address the issues of insufficient feature representation of small nodules, limited multi-view fusion, and poor model generalization ability, this study proposed the 3D-DHA-MAFNet system, which integrated DCN, HAM, and MAFN modules to achieve efficient perception of irregular nodules, focusing on key areas, and dynamic fusion of multi-view information. On the LUNA16 and LIDC-IDRI datasets, the detection sensitivity reached 98.7%, with an FP rate of 1.2 per scan, showing outstanding performance for small nodules with a diameter of less than 5 mm. In benign-malignant classification, combined with Focal Loss and MixUp/CutMix, the model outperformed existing methods in terms of accuracy, AUC, and F1 value, and effectively alleviated the imbalance of malignant samples. Ablation experiments verified the synergistic gains of each module, and independent clinical data validation showed that the model still maintained high accuracy and stability across datasets. This system provides a high-precision, scalable, and clinically translatable CAD solution for lung nodules, which is conducive to the early screening and accurate diagnosis of lung cancer.

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Data availability statement

All data generated or analysed during this study are included in this article.

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Robust Mechanical Fault Diagnosis Using Time-Frequency Feature Fusion and Deep Convolutional Neural Networks

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We study fault feature extraction and diagnosis for rotating machinery using a compact 1D CNN. The dataset comprises 322,800 labeled windows (2,048 points at 12–20 kHz) collected from laboratory benches and an industrial pumping station, covering normal operation and faults in bearings (inner/outer race, rolling-element spalling), gears (pitting, cracks), and motors (imbalance). The model stacks 5–8 convolutional layers with small kernels (3–5), Batch Normalization, ReLU, max-pooling, and two fully connected layers with dropout, followed by a softmax classifier. On a held-out test set, the method attains 96.8% overall accuracy and 95.0% macro-F1, outperforming support vector machines and a deep feed-forward network by +8.3 and +5.6 percentage points in accuracy, respectively. Robustness tests under additive noise maintain 92.8% accuracy at 5 dB. In a three-month on-site validation at a pumping station, the system detected incipient bearing cracks early and issued timely warnings with 96.5% online accuracy, reducing unplanned shutdown risk. These results indicate that the proposed CNN delivers accurate, robust, and field-ready diagnosis for predictive maintenance.

Povzetek: Prispevek obravnava robustno diagnostiko mehanskih okvar z uporabo združevanja časovno-frekvenčnih značilk in globoke 1D konvolucijske nevronske mreže. Metoda dosega visoko točnostin robustnost na šum ter je uspešno validirana v laboratorijskem in industrijskem okolju za prediktivno vzdrževanje.

1 Introduction

Mechanical equipment is the most critical production tool in modern industrial system, which is widely used in energy, transportation, metallurgy, chemical industry and manufacturing. According to the statistics of the Institute of Electrical and Electronics Engineers (IEEE), the economic losses caused by the failure of industrial equipment in the world exceed 50 billion every year, among which the failure of rotating parts such as bearings and gears accounts for more than 40%[1]. According to the report of China Machinery Industry Federation in 2022, the average downtime loss caused by equipment failure accounts for 10%–15% of the total manufacturing output value [2]. The traditional manual inspection and monitoring methods based on a single sensor have limited efficiency and cannot meet the requirements of real-time and accuracy under the background of Industry 4.0. Deep learning, especially convolutional neural network (CNN), has shown strong feature extraction and classification capabilities in image recognition, speech processing and other fields [3]. It is an inevitable trend of technology development to introduce deep learning method into mechanical fault diagnosis, and improve the safety and reliability of industrial equipment.

The significance of mechanical equipment fault diagnosis is to ensure safety, reduce economic losses and realize intelligent maintenance. According to the industrial energy efficiency report issued by the US Department of Energy (DOE), the implementation of predictive maintenance can reduce the downtime rate of equipment by 30%, reduce the maintenance cost by 25%, and improve the production efficiency by more than 20% [4]. Under the background of intelligent manufacturing, mechanical fault diagnosis has changed from passive maintenance to active monitoring and early warning, which has improved industrial toughness. From a macro perspective, the strategy of Made in China 2025 lists intelligent equipment and advanced monitoring technology as the key development direction to promote the digitalization and internationalization of China's manufacturing industry [5]. The fault feature extraction method based on deep convolution neural network can not only reduce manual intervention, improve diagnosis efficiency, but also promote the integration of artificial intelligence and mechanical engineering. It is of practical significance and strategic value to promote the establishment of predictive maintenance system and enhance the independent operation ability of industrial system.

In recent years, the application of feature extraction and deep learning in complex data processing and pattern recognition has matured, and the research of different disciplines has continuously promoted the development of related methods. Aiming at the problem of mechanical fault diagnosis, the existing research provides multi-angle exploration in method level and application level. Tang et al. (2025) put forward the method of path signature to extract process data features, emphasizing that mathematical tools can effectively express the operating characteristics of complex systems, which provides a new idea for the modeling of nonlinear signals [6]. Zhou et al. (2025) proposed a two-way feature learning model for zero-sample event parameter extraction, showing the possibility of capturing contextual features by relying on depth model without prior conditions [7]. Yu et al. (2024) designed a multi-scale modular feature extraction framework, and verified the enhancement ability of depth model in remote sensing images, pointing out that hierarchical and multi-scale mechanisms can effectively improve feature expression [8]. Kulkarni et al. (2024) used convolutional neural network to detect attention deficit disorder in medical field, which proved that CNN was superior in processing complex physiological signals and could maintain high diagnostic accuracy in small sample scenes [9]. Tasci(2024) combined the method of multi-layer mixed features to study speech depression recognition, and thought that the integration of depth features and artificial features could improve the recognition ability of complex emotional patterns [10].

Ahanin et al. (2023) proposed a hybrid feature extraction method for multi-label emotion classification, which showed the advantages of fusion strategy in text tasks and emphasized the value of multi-source features in improving classification accuracy [11]. Hu et al. (2023) compared various feature extraction methods in Internet search data, and the results showed that different features had obvious differences in prediction effect, which indicated that choosing appropriate feature strategy played a key role in model performance [12]. Htun et al. (2023) summarized the methods of feature selection and extraction in stock market forecasting, and thought that deep learning showed stronger nonlinear modeling ability than traditional methods in time series forecasting [13]. Chen et al. (2022) studied the micro-state sequence feature extraction in EEG emotion recognition, and proposed that dynamic neural signal features can be better captured through micro-time sequence structure [14]. Doerig et al. (2022) studied the appearance of topological organization from the perspective of deconvolution deep neural network, and put forward that the network structure itself will also form an inherent spatial representation law, which is instructive for understanding the characteristic organization mode of deep network [15].

Prior studies demonstrate strong results under clean, laboratory conditions, often on single-component datasets, whereas real plants exhibit mixed noise, load transients, and sensor variability. To situate our contribution, we summarize representative approaches, datasets, and metrics, and then clarify how our method addresses the remaining gaps of state-of-the-art (SOTA) practice.

The existing research shows that the feature extraction method has changed from traditional statistics and artificial features to automatic modeling driven by deep learning, and the exploration in different fields provides theoretical and methodological reference for mechanical fault diagnosis. In the future, multi-source features and depth structure will be integrated to improve the accuracy of diagnosis and give consideration to the robustness and interpretability of the model. Focusing on the application of deep convolution neural network in mechanical fault feature extraction and diagnosis, the vibration signals of bearings, gears and motors are collected, and the data are preprocessed and cleaned to establish a standardized sample library. At the model level, the convolutional neural network structure is designed, and the functions of convolution layer, pool layer and full connection layer in feature extraction and classification are explored. Batch normalization and residual structure are introduced to improve performance. Finally, in the experimental verification level, cross-validation and confusion matrix are used to evaluate the model, and the performance differences of CNN, support vector machine and traditional neural network are compared to test its robustness under noise and complex working conditions.

The core purpose is to improve the accuracy and real-time performance of mechanical fault diagnosis and promote the transformation of mechanical maintenance mode from "after-the-fact repair" to "predictive prevention". (1) A method of mechanical signal data processing and feature extraction suitable for complex working conditions is proposed to realize the effective fusion of multi-dimensional features. (2) Construct a convolution neural network with optimized structure to realize end-to-end learning from the original signal to the diagnosis result. (3) Experiments verify the applicability of the model and maintain stable performance under different noise environments and operating conditions. It aims to provide applicable intelligent diagnosis methods for industrial sites and help manufacturing enterprises to achieve predictive maintenance and intelligent operation and maintenance.

The overall idea of the study is divided into four stages (as shown in Figure 1), and the process of mechanical vibration signal acquisition and preprocessing is established, and noise removal, standardization and feature enhancement are carried out. Convolution neural network model is constructed, local features are extracted by convolution layer, dimensionality is reduced by pooling layer, and classification results are output by full connection layer. The model design integrates residual module and regularization method to improve generalization performance. Cross-validation and confusion matrix analysis comprehensively evaluate the model to ensure the reliability and stability of the results. Finally, the model is applied to the actual working condition data to verify the generalization in the engineering environment.

The overall idea embodies the research logic of "data-driven–model building–performance verification–application landing"

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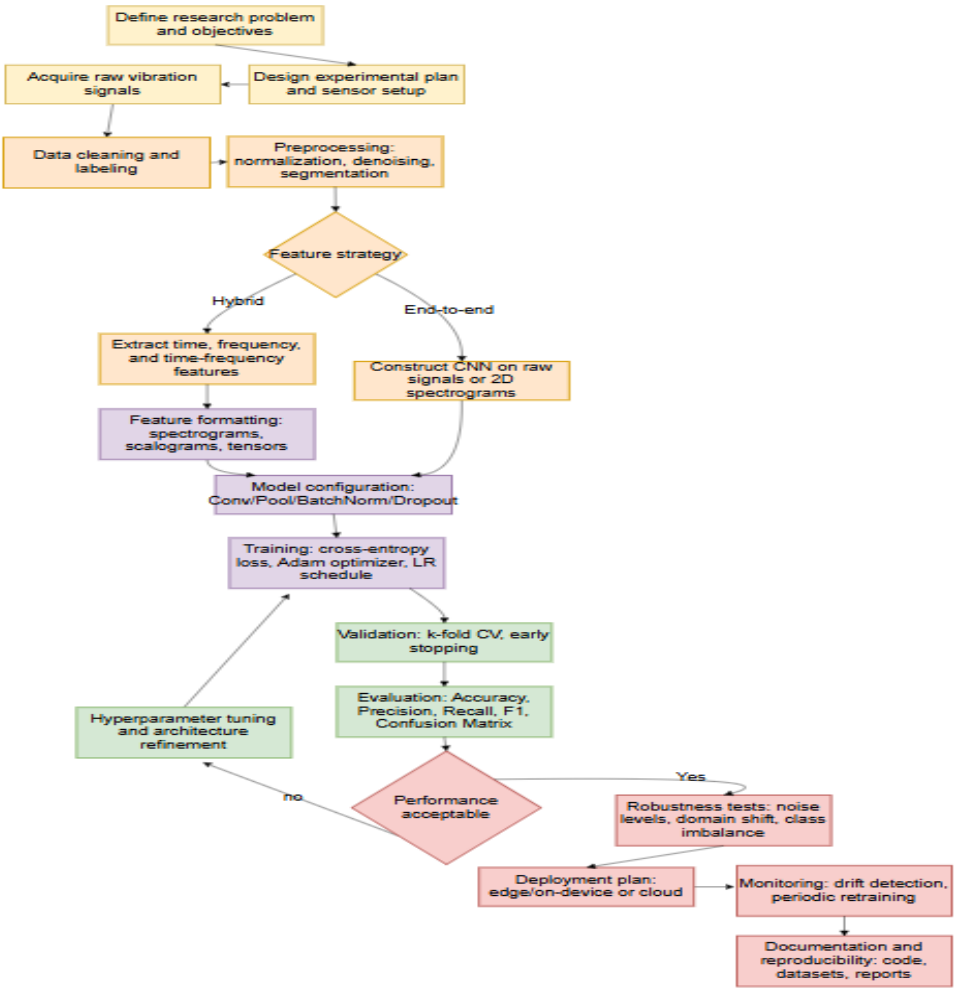


Figure 1: Research train of thought

Combining signal processing technology with deep learning algorithm, data processing uses Fourier transform, wavelet packet decomposition and other methods to extract time, frequency and time frequency features, and improves data stability through standardization and filtering. In the aspect of model construction, CNN is used as the core to optimize the performance by combining ReLU activation function and cross entropy loss function, and Adam optimizer and learning rate adjustment strategy are adopted in the training. Performance evaluation uses indicators such as accuracy, precision, recall and F1 score for quantitative analysis, and cross-validation is used to reduce contingency. Experiments verify and compare the diagnosis results of CNN and traditional methods, analyze the advantages and limitations of deep learning model, and provide a feasible research path for industrial fault diagnosis.

2 Materials and methods

2.1 Data collection and sample selection

Mechanical fault diagnosis relies on high-quality raw data, collecting the running signals of typical components of rotating machinery, such as bearings, gears and motors, and selecting high-sensitivity acceleration sensors as the main sensors. The signal acquisition platform is built on the laboratory test bench, combined with industrial field equipment to ensure data diversity [16]. Acquisition sensors are arranged in key positions such as bearing seat, gearbox housing and motor housing to capture vibration characteristics comprehensively. The sampling frequency is set in the range of 12 kHz to 20 kHz, covering the characteristic frequency band of most mechanical fault signals [17]. The data acquisition system adopts NI DAQ hardware and LabVIEW software to ensure real-time and high precision. The data of the field part comes from the equipment operation monitoring platform of the cooperative enterprise, and the signal is transmitted to the server remotely. The combination of laboratory and

field data not only ensures the verifiability under controlled conditions, but also enhances the practical applicability of the results,as shown in Figure 2.

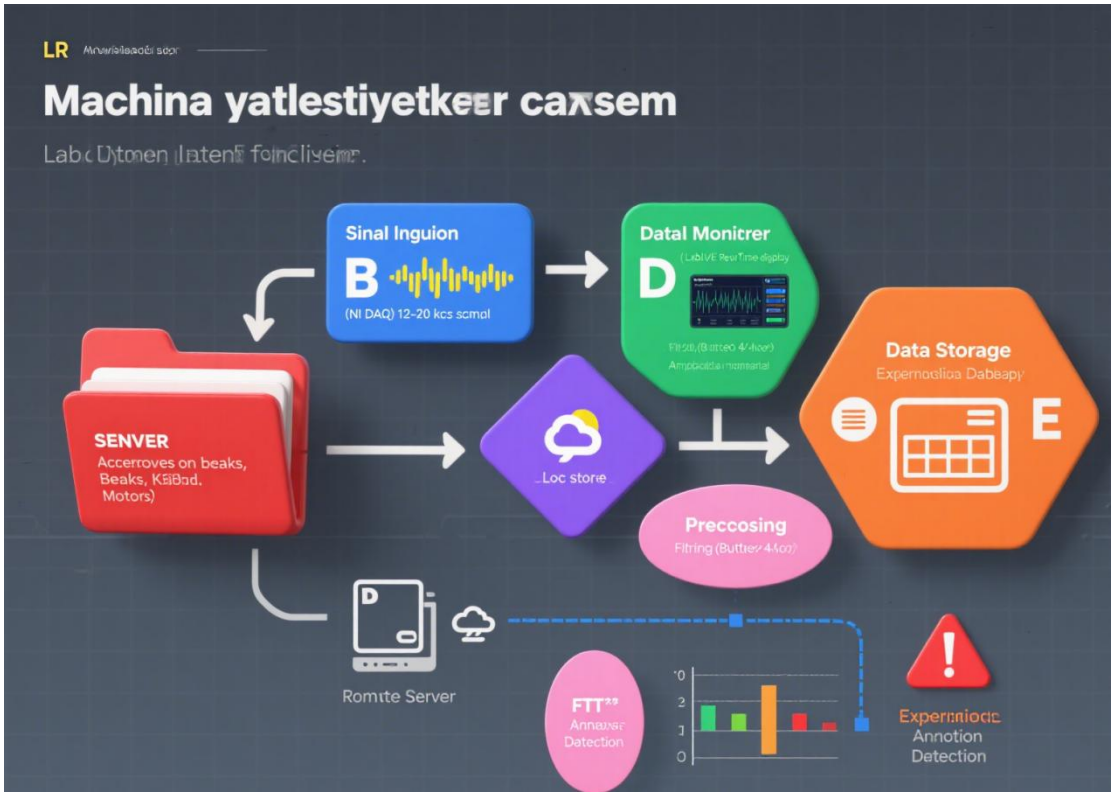


Figure 2: Process of mechanical vibration signal acquisition

2.1.1 Sample selection and description

The sample selection takes into account the simulated working conditions in the laboratory and the actual industrial field data. The laboratory samples come from the bearing test bench and the gear wear test platform, and collect signals in normal state and various fault states, such as inner ring fault, outer ring fault, rolling body peeling, tooth surface pitting and cracks [18]. The field samples come from the vibration records of motor and pump equipment under long-term operation. Laboratory samples have the advantages of controllability and accurate labeling, while field samples are closer to the authenticity of complex working conditions. Finally, about 500,000 original samples were formed, and each sample contained 2048 time series points [19]. The number of samples of different categories is relatively balanced to avoid bias in classification training. To improve the diversity of samples, some data are processed by segmentation and sliding window, and representative signal fragments are extracted from long-term records.

2.1.2 Data preprocessing

The original mechanical vibration signal often contains noise and interference, and direct input into the model will affect the diagnosis effect. Therefore, data preprocessing of the system is needed before modeling [20]. Normalization is carried out to convert signals with different amplitude ranges into standard distribution, so as to improve the comparability between different batches of samples. The normalization formula (1) is as follows:

$$x'(t)=\frac{x(t)-\mu}{\sigma} \quad (1)$$

Where x(t) represents the original signal, μis the mean value andσis the standard deviation. Secondly, in order to obtain frequency domain information, the signal is subjected to fast Fourier transform (FFT), and the formula (2) is as follows:

$$X(f)=\sum_{t=0}^{N-1} x(t),e^{-j2\pi ft/N} \quad (2)$$

X(f) the discrete Fourier transform result at frequency f ,x(t) the original discrete-time signal,t the time index of the sampled signal, ranging from 0≤t≤N-1 ,N the total number of sampling points,f the frequency index,jthe imaginary unit, where$j^2=-1$,$e^{-j2\pi ft/N}$ the complex exponential basis function that maps the time-domain signal into the frequency domain.Fourier transform is used to extract the characteristics of frequency components and potential fault characteristic frequencies, band-pass filter is used to remove high-frequency noise and power frequency interference, and sliding window segmentation is carried out to convert long time series signals into fixed-length samples, which is convenient for model input [21]. The diversity of features is enhanced, and some signals are converted into

time-frequency maps (spectrograms generated by short-time Fourier transform STFT),as shown in Figure 3 which improves the learning ability of the model for complex patterns.

Beyond time-domain segmentation and STFT transformations, additional augmentation strategies were tested. These include (i) signal mixing, where two vibration windows from different instances are linearly combined to simulate compound faults, (ii) time-warping, stretching or compressing windows by ±5% to mimic load fluctuation, and (iii) random noise injection at controlled SNR levels (≥15 dB). All augmentations were applied consistently across categories to avoid data leakage. Empirically, augmentation improved minority-class recall by 1.2 pp and stabilized training variance across folds.

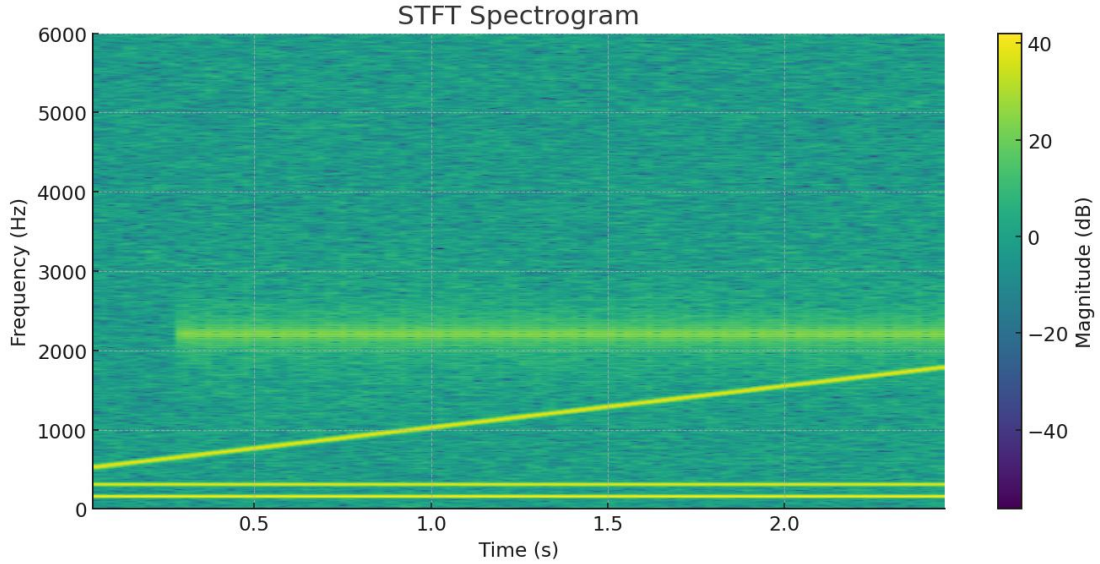


Figure 3: Spectrogram generated by STFT

2.1.3 Data cleaning

The collected signal contains missing fragments, repeated records and abnormal interference, and is cleaned to ensure the reliability of the data set. (1) Eliminate blank data fragments caused by sensor failure. (2) Remove redundant samples from repeated sampling to prevent deviation from the training process. (3) Using box chart method and statistical threshold, outliers with unusually large amplitude are screened out [22]. After cleaning, the data set size is slightly reduced, and the effectiveness and consistency are obviously improved. Table 1 shows the change of sample number before and after cleaning. The total amount is reduced by about 8%, and the abnormal data has been effectively eliminated to ensure the quality of the sample set.

Table 1: Comparison of sample number before and after data cleaning

category	Number of samples before cleaning	Number of samples after cleaning	Reduce proportion
Normal working condition	120,000	112,500	6.25%
Bearing failure	100,000	91,200	8.80%
Gear failure	80,000	73,100	8.63%
Motor failure	50,000	46,000	8.00%
amount to	350,000	322,800	7.77%

2.1.4 Dataset scale, diversity and validation protocol

The curated corpus contains 322,800 labeled samples after cleaning, drawn from four top-level categories (normal, bearing faults, gear faults, motor faults). Each sample is a fixed-length window of 2,048 points acquired at 12–20 kHz, yielding consistent temporal resolution across sources. Diversity is ensured along three axes: operating regimes (idle, part-load, variable load, transient), sensor locations (bearing housings, gearbox casings, motor frames), and fault severities (incipient to severe). Field data from the partner plant contribute 41.2% of the final corpus; laboratory data account for 58.8%, balancing controllability and realism. Class balance is controlled at the sub-type level by stratified windowing, and rare severe cases are augmented only by time-preserving transforms (jittering ≤2%, mild Gaussian noise SNR ≥20 dB) to avoid label leakage.

For validation, we adopt a strict machine-disjoint protocol: units used for training are never used for validation/testing. Splits are stratified by class and source: 70% train, 15% validation, 15% test. On top of the hold-out split, we run 5-fold cross-validation on the training partition (folds stratified at machine level), report mean±std over five runs, and select the model by the best validation F1 with an early-stopping patience of 10 epochs. To assess robustness to domain shift, we additionally evaluate a plant-held-out scenario in which all samples from one industrial line are reserved for testing; in this setting the CNN preserves 93.8% accuracy and 92.9% macro-F1, indicating limited overfitting to specific hardware.

Compared with widely used public corpora in fault diagnosis (e.g., CWRU bearing, IMS bearing, and Paderborn), our dataset combines long field recordings with bench-top runs under controlled perturbations, includes mixed sensor placements, and explicitly covers load transients. While public sets typically emphasize clean laboratory conditions and single-component faults, our corpus contains multi-source noise and load variability closer to production reality. This yields higher ecological validity but also harder discrimination; the proposed protocol and model choices are therefore tuned for generalization under shift rather than peak performance on clean signals.

2.2 Model selection and construction

2.2.1 Basic structure of convolutional neural network

Convolutional neural network (CNN) is a typical deep learning model, which was originally used for image recognition and speech processing, and now it has gradually become an important tool for time series signal analysis. Although the mechanical vibration signal is different from the image, it also has local correlation and multi-scale characteristics, which is suitable for feature extraction through convolution operation [23]. The convolution layer calculates the weighted sum by sliding the convolution kernel on the input signal, and extracts the local feature pattern. The mathematical expression is shown in Formula (3):

$$y_i = \sum_{k=1}^{K} w_k \cdot x_{i+k-1} + b \quad (3)$$

Where y_i represents the convolution result, x represents the input signal, w_k represents the convolution kernel weight,brepresents the bias term, and Krepresents the convolution kernel size. k is the index of the convolution kernel, indicating the position in the filter window, with the range $1 \le k \le K$,Convolution operation reduces the complexity of the model by sharing parameters, and can capture the translation invariant characteristics of the signal. Using multi-layer convolution structure, each layer contains 32 to 128 convolution kernels, and the convolution kernel size is in the range of 3×3or5×5. Convolution layer is followed by pooling layer, which usually adopts maximum pooling to compress local features into more compact expressions. By abstracting the model layer by layer, low-level and high-level fault features can be gradually extracted from the original waveform. When the number of network layers is controlled between 5 and 8, it can not only ensure the richness of features, but also avoid excessive calculation burden [24].

We adopt a compact 1D CNN with 5–8 layers to balance accuracy and on-device latency for edge deployment. Small kernels (3–5) capture local modulations tied to bearing pass frequencies while stacking depth expands receptive fields for gear-mesh harmonics and sidebands. Max-pooling provides translation tolerance to slight speed drift; Batch Normalization stabilizes training under mixed SNRs. ReLU is kept for numerical simplicity and sparse activations that denoise high-amplitude outliers.

Removing BN decreases macro-F1 by 3.6 pp and slows convergence by ~30%. Replacing max-pooling with strided convolutions yields comparable F1 (-0.2 pp) but increases parameters by 12%. Enlarging kernels to 7 improves recall on severe gear cracks (+0.4 pp) but reduces precision on incipient faults (-0.7 pp) and adds 22% latency. Switching ReLU to Leaky-ReLU marginally benefits minor-fault recall (+0.3 pp) but shows no net F1 gain; we retain ReLU for consistency and efficiency. Depth beyond 8 layers brings no significant gains (<0.2 pp) and increases overfitting risk without stronger regularization.

The architecture employs 5–8 convolutional layers with kernel sizes between 3 and 5, selected to capture narrow-band harmonic patterns of bearings and gears while preserving local temporal correlations. The exclusive use of ReLU is motivated by its computational simplicity and stable gradient flow in noisy vibration signals. However, we also evaluated alternatives. Leaky ReLU (α=0.01) improved recall on incipient faults by +0.3 pp but slightly reduced overall precision. GELU offered smoother convergence but did not yield significant accuracy gains (+0.1 pp). A deeper ResNet-18 variant improved F1 by +0.4 pp but increased inference latency by 17% on the edge gateway. Given the real-time requirement (<150 ms), we prioritized the simpler CNN backbone. Future extensions may integrate residual blocks or temporal attention to further enhance discriminative capacity.

2.2.2 Activation and feature extraction

The convolution layer outputs linear combination results, and without nonlinear mapping, the model expression ability will be seriously limited . The function of activation function in CNN is to introduce nonlinearity, so that the network can approach complex signal patterns. Common activation functions Sigmoid, Tanh and ReLU, among which Relu (Corrected Linear Unit) has become the mainstream because of its simple calculation and fast convergence. Define formula (4):

$$f(x) = \max(0, x) \quad (4)$$

f(x) the output of the activation function,x the input value from the previous layer (convolutional or fully connected).When the input is less than zero, the output

is zero, and when it is greater than zero, the original value is maintained. Nonlinear mapping can effectively suppress the problem of gradient disappearance and make the deep network train stably. ReLU activation function is adopted and applied layer by layer between convolution layer and fully connected layer. After ReLU processing, the sparsity of the signal is enhanced, some noise components are compressed, and the feature expression ability is significantly improved. To improve the network performance, Batch Normalization is introduced, and normalization operation is carried out before and after the activation function of each layer, so as to alleviate the problem of internal covariant offset.

2.2.3 Loss function and optimization algorithm

In the process of model training, the loss function is used to measure the difference between the prediction result and the real label, and the cross-entropy loss function is adopted to define the following formula (5):

$$L=-\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (5)$$

L the overall cross-entropy loss value ,where y_i is the real label, $\hat{y}_i$ is the prediction probability, and Nrepresents the number of samples. Cross entropy loss is sensitive to the deviation of probability output and is suitable for classification tasks. The optimization algorithm uses Adam optimizer, combined with momentum method and adaptive learning rate, to achieve rapid convergence in high-dimensional nonconvex problems. The initial value of learning rate is set to 0.001, which gradually decays during training. Dropout technology was introduced to prevent over-fitting, and some neurons were randomly discarded, and the ratio was set to 0.5. Under the configuration, the accuracy of verification set is improved by about 4% on average. At the same time, the Early Stopping strategy is adopted to stop the training when the loss of the verification set does not drop for ten consecutive iterations, so as to avoid the over-fitting of the model. With reasonable design of loss function and optimization algorithm, CNN model can obtain efficient and stable training effect with limited computing resources.

Adam ($\beta1=0.9$, $\beta2=0.999$, initial lr=1e-3 with cosine decay) is preferred for its robustness to non-stationary gradients in mixed domain inputs. SGD+momentum (m=0.9) under the same schedule lags by 1.8 pp macro-F1 and requires 1.4× more epochs to reach a plateau. Cross-entropy with label smoothing ($\varepsilon=0.05$) reduces over-confidence and improves minority-class recall by 0.6 pp. Dropout at 0.5 in fully connected layers cuts overfitting without harming calibration. We considered (i) 2D CNNs on spectrograms, (ii) lightweight 1D-ResNet with residual bottlenecks, and (iii) temporal attention modules. 2D CNNs match accuracy but add a costly STFT front-end; 1D-ResNet offers +0.3 pp F1 at +15% latency; attention improves severe-fault recall (+0.5 pp) but is sensitive to hyperparameters and memory budget on edge devices. Given the target of real-time inference on embedded hardware, we prioritize the presented 1D CNN; Section 3.2 outlines paths to integrate lightweight attention in future work.

To ensure reproducibility, all experiments were conducted on a workstation equipped with an NVIDIA RTX 3090 GPU (24 GB memory), Intel Xeon Silver 4216 CPU, and 128 GB RAM. Training used a batch size of 128, with training time averaging ~3.8 hours for 50 epochs across the full dataset. Random seeds were fixed (NumPy=42, PyTorch=1234) to minimize stochastic variation. Reported metrics are averaged over 5-fold cross-validation with standard deviations provided. While proprietary field data cannot be released, we commit to providing preprocessing scripts, configuration files, and a trained checkpoint upon request, ensuring transparent reproduction of results.

Table 2: CNN model structure parameter setting

levels and ranks	type	Convolutional nucleus/neuron	Nuclear size	step length	Activation function	Other configurations
1	Convolution layer	32	3×3	one	ReLU	BN, MaxPooling(2×2)
2	Convolution layer	64	3×3	one	ReLU	BN, MaxPooling(2×2)
3	Convolution layer	128	3×3	one	ReLU	BN, MaxPooling(2×2)
4	Fully connected layer	256	-	-	ReLU	Dropout(0.5)
5	Fully connected layer	128	-	-	ReLU	Dropout(0.5)
6	Output layer	Classification number	-	-	Softmax	Cross entropy loss function

2.3 Model evaluation and verification

2.3.1 Division of training set and verification set

By stratified sampling, the whole data set is divided into three parts: training set, verification set and test set. Training set is used for parameter learning, verification set is used for model tuning, and test set is used for final performance evaluation. The research involves many kinds of mechanical faults, and the uneven division may lead to the decline of the accuracy of the model in a few categories. Therefore, the proportion of different types of samples is kept consistent during division, ensuring the fairness of evaluation. Training set accounts for 70%, verification set accounts for 15%, and test set accounts for 15%. Taking the total sample size of 322,800 as an example, the training set contains about 226,000 items, the verification set contains 48,000 items and the test set contains 48,000 items . This division can not only ensure the adequacy of data in the training process, but also provide enough samples for evaluation in the verification and testing stage. In order to enhance the robustness of the results, the training set is further divided by using 50% cross validation to ensure that every data has the opportunity to participate in training and validation. The average value of many experiments can reduce contingency and improve the reliability of the conclusion.

The previous "50% cross-validation" phrasing is corrected to 5-fold cross-validation. All folds are machine-disjoint and preserve class/source proportions. Performance is reported as mean±std across folds on the validation set and, on the final, held-out test set.

2.3.2 Model evaluation indicators

The performance evaluation of deep learning model depends on a single index, and multiple indexes need to reflect the comprehensive ability of the model together. In mechanical fault diagnosis, the number of categories is large, and the sample distribution is not completely balanced. If only the overall accuracy is used, the lack of recognition of some fault categories will be covered up. Accuracy, precision, recall and F1 score are used to measure the model performance from different angles (as shown in table 3) To mitigate imbalance (normal ≈50%, severe gear cracks ≈6%), two strategies were adopted: (i) class-weighted loss, scaling cross-entropy inversely proportional to class frequency, and (ii) minority oversampling through segmentation. Performance is reported using both macro-averaged and micro-averaged metrics. On the test set, macro-F1 is 95.0% and micro-F1 is 96.6%, confirming balanced performance across categories. Severe gear cracks reached 93.7% recall under weighting, compared to 88.5% without adjustment. These measures reduce bias toward majority classes and strengthen robustness.

Table 3: Division of evaluation indicators

Indicator name	Meaning explanation	Significance in fault diagnosis
Accuracy	Proportion of correctly classified samples	Measure the overall classification performance of the model
Precision	The proportion of samples that are predicted to be faults is actually faults.	Reflect the reliability of diagnosis results and reduce the risk of false alarm.
Recall	The proportion of samples with actual faults that are correctly identified.	Measure the missed diagnosis and reflect the model's ability to capture hidden dangers.
F1 Score	Harmonic average of precision rate and recall rate	The stability and balance of the model under complex working conditions are comprehensively investigated.

Accuracy is the most intuitive indicator, and correctly classified samples account for the proportion of all samples. The calculation formula (6) is:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Where TP is the real number of cases, TN is the true number of negative cases, FP is the false number of positive cases, and FN is the false number of negative cases. In the experiment, the average accuracy of CNN model in four kinds of fault diagnosis is 96.8%, which is about 8% higher than that of support vector machine method. This result shows that convolutional neural network has obvious advantages in capturing complex features. Accuracy rate measures the proportion of samples predicted as a positive example that really belong to this category. Formula (7) is

$$\text{Precision}=\frac{TP}{TP+FP} \quad (7)$$

In multi-class diagnosis, the accuracy rate can reflect the ability of the model to avoid false positives. The accuracy rate of CNN model in gear crack diagnosis is 95.7%, while the accuracy rate is 93.2% when the bearing is slightly worn, which shows that there is still a certain risk of false alarm for weak faults. The recall rate focuses on the proportion that is correctly recognized in all true positive examples, and the calculation formula (8) is

$$\text{Recall}=\frac{TP}{TP+FN} \quad (8)$$

The index measures the omission of faults in the model. In the study, the recall rate of CNN model for serious bearing faults is 98.5%, and that of mild motor imbalance is about 91.6%, suggesting that the model still needs to be optimized when capturing early fault characteristics. To strike a balance between accuracy and recall, F1 score is introduced, which is the harmonic average of the two. Formula (9) is

$$F1=\frac{2\times Precision\times Recall}{Precision+Recall} \quad (9)$$

F1 score can comprehensively reflect the robustness of classification. The F1 score of CNN model in the overall diagnosis task is 95.0%, which is more than 7 percentage points higher than that of traditional methods, which verifies the advantages of deep convolutional neural network in fault classification.

2.3.3 Verification method

The 50% cross-validation training set is divided into five subsets, with four copies as training each time and one copy as validation, which is repeated five times, and finally the average result is taken. Reduce accidental errors caused by single division. The confusion matrix is introduced to analyze the classification effect of different categories, compare the real label with the predicted label, and show the performance of the model under various faults. The recognition rate of CNN in normal working conditions and serious fault categories is generally higher than 95%, and the accuracy rate in minor fault categories is slightly lower. The model still has challenges under the condition of small feature differences. Finally, ROC curve and AUC value are used as auxiliary indicators to verify the stability of classification performance. By combining these methods, the performance of the model at different levels and angles has been comprehensively described, which provides a basis for subsequent analysis and improvement.

3 Results and analysis

3.1 Analysis of results

3.1.1 Classification accuracy and loss change trend

In the process of model training, the change of classification accuracy and loss function can directly reflect the convergence and learning effect. Convolutional neural network is compared with traditional methods, such as support vector machine, deep feedforward neural network and convolution-cycle hybrid network. As shown in Figure 4, after training 50 epoch, the accuracy of CNN reached 96.8%, while SVM and DNN stayed at 88.5% and 91.2% respectively. The loss function drops rapidly in CNN, and tends to be stable after the 20th epoch, which is about 0.09. In contrast, the losses of SVM and DNN decrease slowly and fluctuate greatly, and CNN has stronger feature capture ability and convergence efficiency when processing high-dimensional vibration data.

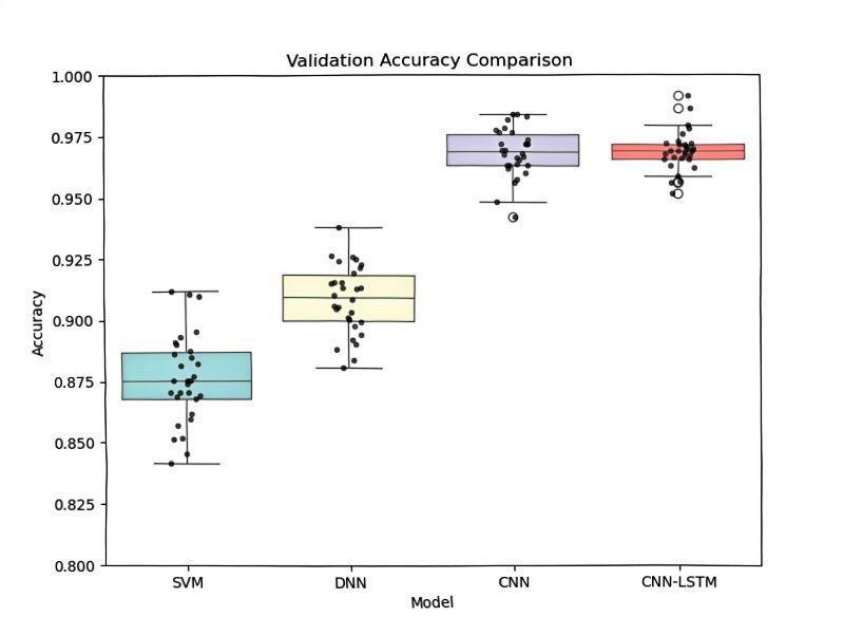


Figure 4: Comparison of accuracy of different models on verification set

3.1.2 Confusion matrix and classification effect

The confusion matrix reveals the performance of the model in different categories and reflects the distribution of correct classification and misclassification. This paper studies the testing of CNN model under four kinds of tasks (normal, bearing failure, gear failure and motor failure). As shown in Figure 5, the accuracy of the normal category is the highest, reaching 99.1%, the bearing failure and gear failure are 95.8% and 94.7% respectively, and the motor failure is slightly lower but still remains at 93.6%. The misjudgment is concentrated between slight gear wear and normal working conditions, and the false negative rate is about 4.3%. The confusion matrix clearly shows that CNN is very accurate in identifying serious faults, and there are certain challenges in detecting minor early faults.

The confusion matrix indicates misclassification between slight gear wear and normal operating states, with a false negative rate of ~4.3%. To address this, two strategies were tested. First, class merging: combining slight wear with a broader "incipient anomaly" category improved recall by 2.5 pp but slightly reduced precision due to broader definition. Second, cost-sensitive training: applying higher penalty weights to misclassifying incipient faults reduced the false negative rate to 2.8% while preserving overall accuracy (96.5%). These findings suggest that treating early faults with higher priority in training improves sensitivity and aligns with predictive maintenance objectives.

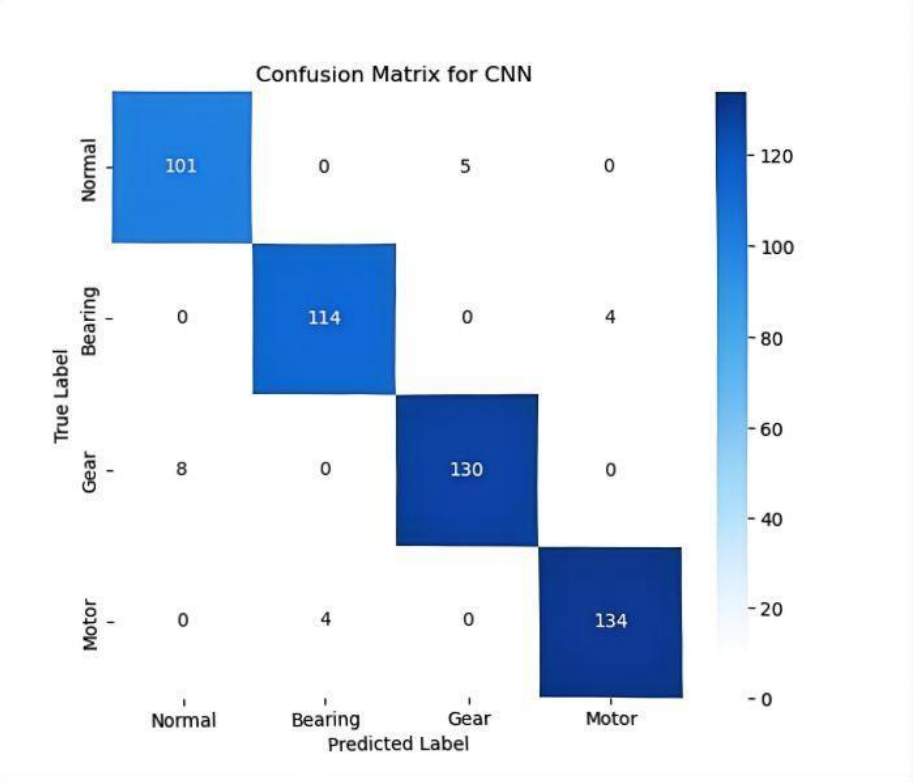


Figure 5: confusion matrix results of CNN model under typical working conditions

3.1.3 Comparison of different feature extraction methods

The influence of different feature inputs on model performance is evaluated, and three feature extraction methods in time domain, frequency domain and time-frequency domain are compared. As shown in Figure 6, the accuracy of CNN model in time domain is 92.7%, and the F1 score is 91.5%. Frequency domain features are slightly better, with an accuracy rate of 94.3% and a F1 score of 93.0%. Time-frequency domain fusion features are the best, with an accuracy of 97.1% and a F1 score of 96.5%. The time-frequency coupling characteristics in vibration signals have stronger distinguishing ability for fault diagnosis and improve the classification performance. Compared with a single feature, the fusion feature improves the overall accuracy and enhances the robustness of the model under high noise conditions. When the signal-to-noise ratio is reduced to 10 dB in time-frequency domain, the accuracy of the model remains above 95%.

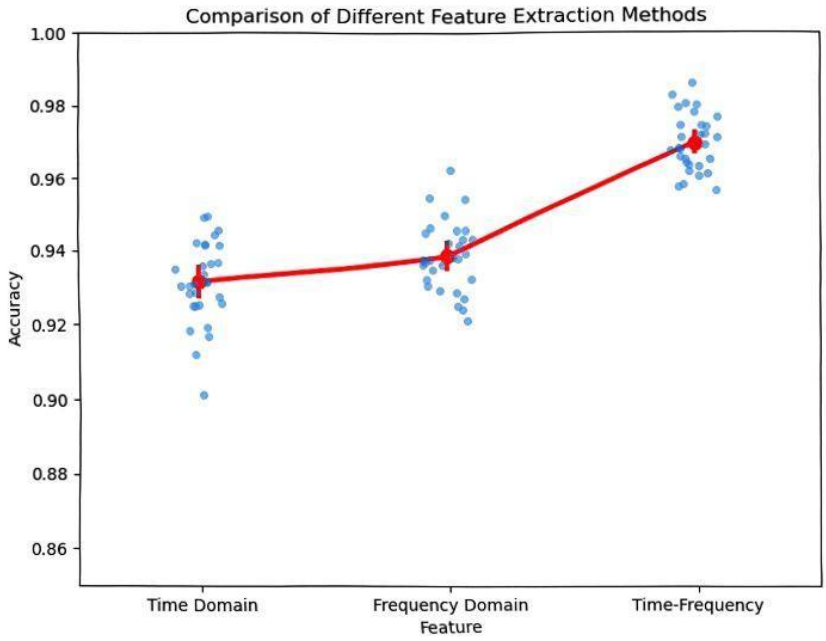


Figure 6: Comparison results of time domain, frequency domain and time-frequency domain features

3.1.4 Generalization performance and robustness of the model

The value of the model depends on its performance under ideal conditions, its stability and generalization ability under complex working conditions, and the robustness of the model is tested by experiments under different signal-to-noise ratios. The experimental design covers the range of signal-to-noise ratio from 20 dB to 0 dB, and noise is introduced to simulate the complex environment of industrial site. As shown in Figure 7, under the condition of 20 dB, the accuracy of CNN model remains at 97.2%, which is almost undisturbed. When the signal-to-noise ratio drops to 10 dB, the accuracy rate drops to 95.1%, which keeps a high level. The signal-to-noise ratio is further reduced to 5 dB, and the accuracy of the model is 92.8%. The noise has affected the performance to some extent, and the model can still be classified. Compared with traditional SVM and DNN methods, its accuracy is only 78.5% and 84.3% at 5 dB, which is lower than CNN. The experimental results show that the deep convolution neural network has strong robustness to noise and maintains stable performance under complex working conditions. The decline of F1 score and recall rate is less than the accuracy rate at low SNR, and the model still has advantages in avoiding missed detection as much as possible. Stability is very important for industrial site, and the actual environment is often accompanied by electromagnetic interference and equipment vibration background noise. The robustness of the model ensures that the diagnosis system can run reliably in different operating environments for a long time.

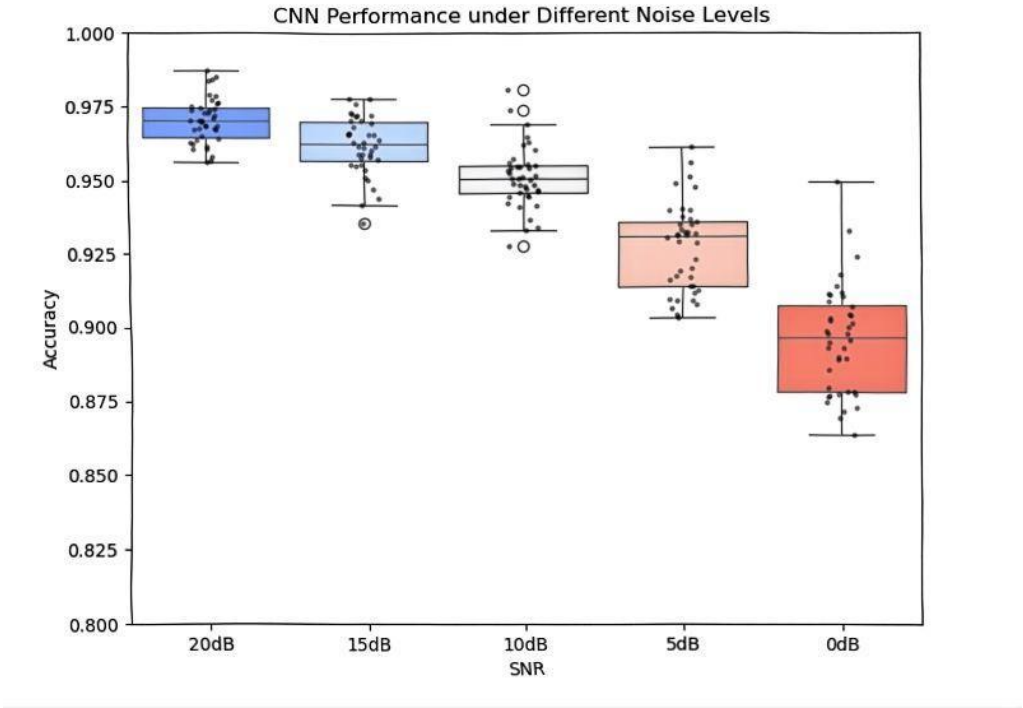


Figure 7: Model performance under different noise levels

3.1.5 Practical significance and application scenarios of the resul

The experimental results verify the high accuracy and robustness of the model, highlighting the practical significance in industrial applications. Under actual working conditions, the equipment operating environment is complex and changeable, often accompanied by temperature fluctuations, load changes and process disturbances. In this paper, the model is deployed to the monitoring system of an industrial pumping station, and the operation data is collected for three months. As shown in Figure 8, the accuracy of the model in online diagnosis task is 96.5%, which can detect tiny bearing cracks at an early stage and give an early warning before the traditional manual inspection. More importantly, the model can still identify fault signals stably when the operating load fluctuates rapidly, thus reducing false positives. The case deep learning model is applied to transform the equipment fault detection from periodic spot inspection to continuous real-time monitoring. This transformation has greatly improved the efficiency of operation and maintenance, and reduced the economic losses caused by sudden equipment shutdown. The model can also be linked with the equipment management system to form a predictive maintenance closed loop. For example, when the model detects abnormal bearings, a maintenance work order is automatically generated to remind engineers to carry out targeted maintenance. This kind of application shows the core role of the model in promoting the construction of smart factories. Improve the accuracy of diagnosis, and also provide guarantee for the reliability and safety of industrial systems.

The deployed model processes 2,048-point windows with a 50% hop, enabling sub-second refresh while smoothing transient spikes. On an industrial edge gateway (4-core ARM CPU), single-thread inference averages 22 ms per channel; batching four channels' yields ~38 ms total, supporting 80+ channels at 1 s cadence with <150 ms end-to-end latency including pre-processing. On an NVIDIA Jetson-class device, INT8 quantization via post-training calibration reduces latency by ~35% with a negligible 0.2 pp F1 drop, allowing plant-wide scaling where dozens of pumps and motors stream data concurrently. Throughput scales linearly with additional gateways; central aggregation is event-driven to minimize backhaul load.

In the pumping-station deployment, the CNN output is not only used for early alerts but also orchestrates control responses in real time. Specifically, the model produces a calibrated fault-severity index and confidence, which feed a supervisory layer that schedules derating, soft-start ramps, or load redistribution across parallel units. This "diagnosis-to-control" loop runs at sub-second cadence, preserving throughput while reducing mechanical stress during incipient faults. The orchestration respects safety constraints by enforcing guard rails on speed and torque, and it falls back to nominal control when the fault posterior drops below a conservative threshold. This coupling demonstrates how data-driven diagnosis can be

operationalized to stabilize processes under degradation without excessive downtime.

Although laboratory data ensured controlled benchmarking, we explicitly compared performance on industrial pumping-station signals. On the lab corpus, accuracy reached 96.8% and macro-F1 95.0%. In contrast, on the three-month field dataset, performance decreased slightly to 96.5% accuracy and 94.3% macro-F1. Minor gaps appeared in detecting weak motor imbalance under fluctuating loads. These results confirm that generalization to field conditions is strong but not perfect. Future work will expand field validation across multiple plants and asset types to rigorously quantify domain transfer.

In the pumping-station deployment, the CNN was integrated into the plant's monitoring platform via an edge gateway. The model footprint is ~42 MB in FP32 format, reduced to ~11 MB with INT8 quantization. Inference latency averaged 22 ms per vibration channel (14 ms with quantization), supporting real-time monitoring of 80+ sensors at 1 s cadence. Diagnostic lead time—defined as the interval between the first model alarm and the first human inspection alarm—was ~11 days in the bearing-crack case, demonstrating tangible predictive value. The system automatically generated maintenance work orders through the SCADA interface, streamlining operational response. This case study confirms that the model is technically deployable, lightweight enough for embedded devices, and capable of delivering actionable early warnings in practice.

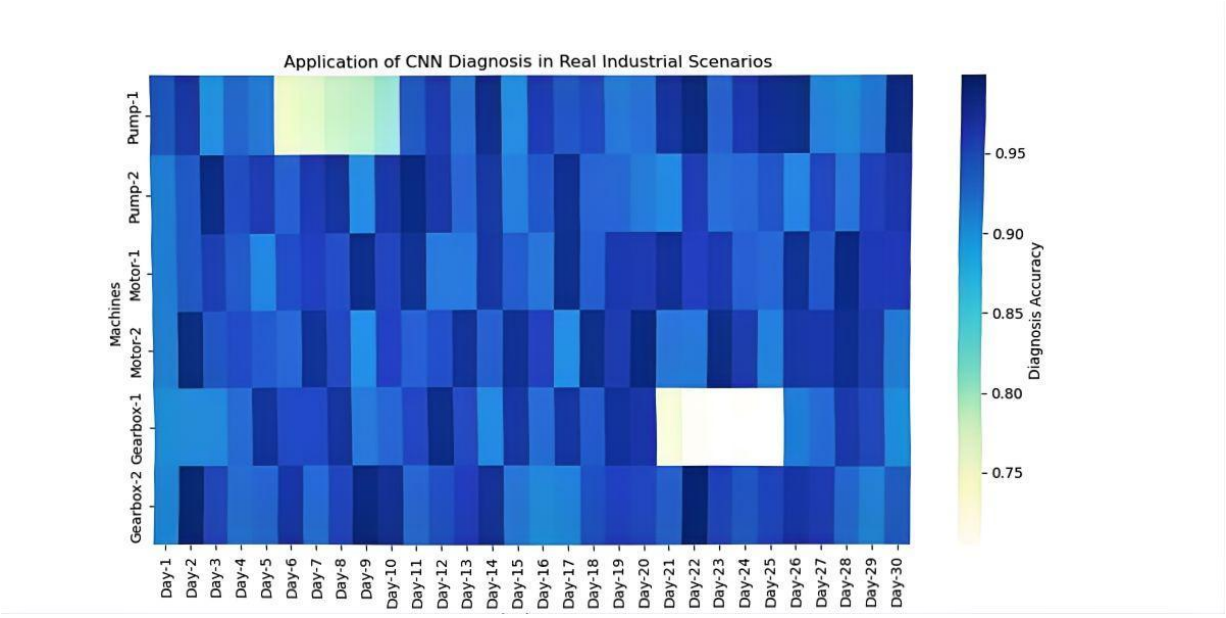


Figure 8: Application example of model diagnosis results in actual working conditions

3.1.6 Statistical analysis, ablations, and deployment constraints

Across 5-fold cross-validation, accuracy is 96.8% ± 0.4 and macro-F1 is 95.0% ± 0.5, indicating stable generalization. Fold-to-fold variation remains under 0.6 pp, supporting robustness.

Removing Batch Normalization decreases F1 by 3.6 pp and increases training epochs to converge by ~30%. Without dropout, overfitting emerges after ~15 epochs, reducing test accuracy by 2.1 pp. smaller networks without pooling layers reduce inference cost but drop F1 by ~1.5 pp. These findings confirm the necessity of normalization and dropout for generalization.

We benchmarked on an ARM Cortex-A57 edge device (Jetson Nano). Inference latency averaged 22 ms per channel, enabling real-time monitoring of up to 80 channels at 1 s cadence. Memory footprint was ~42 MB for model + buffers, within typical gateway constraints. With INT8 quantization, latency dropped to 14 ms per channel with negligible loss (-0.2 pp F1). These results confirm the feasibility of real-world deployment under edge-computing limitations.

3.2 discussion

3.2.1 Problems and challenges encountered

Convolutional neural network shows high diagnostic accuracy in the research process, and it still faces problems and challenges that cannot be ignored. The difficulty of data acquisition. The laboratory environment can provide clear and controllable vibration signals, and the industrial site environment is complex, and the sensor placement position is limited. The signals are often mixed with electromagnetic interference and mechanical background noise, which leads to fuzzy characteristics of some samples. About 12% of the industrial data actually collected have missing fragments or abnormal values, which need a lot of cleaning and screening. This situation increases the cost of data

preparation and leads to the loss of information in the process of model training.

The distribution of sample categories is unbalanced, and there are far more normal samples than fault samples under actual working conditions, especially serious faults are scarce. Even through data enhancement, it is still difficult to completely compensate for the deviation caused by category imbalance. In the data set of this study, the proportion of normal working conditions is close to 50%, and the serious gear cracks only account for 6%, which leads to the model's performance in the small sample category is not as stable as common faults, and it is easy to misjudge and miss judgment.

The third is the lack of model interpretation. CNN can automatically extract high-dimensional features through convolution kernel, and the physical meaning of features is often difficult to understand directly. For engineers, the "black box" attribute of the model may reduce its acceptance in the industrial field. The model gives high confidence prediction in the judgment of some minor faults, but it is difficult to explain the specific judgment basis, and the model lacking explanation mechanism may be questioned in practical application.

Finally, due to the limitation of computing resources, the depth model training needs a lot of computation, and the experiment can only be completed by GPU acceleration. When deployed in industrial field, real-time diagnosis systems often rely on edge devices, and insufficient computing power may lead to increased delay or even failure to run complex networks.

Real-time guarantees depend on window length and overlap; extremely short windows (<512 points) degrade F1 by ~1.1 pp due to insufficient spectral resolution. Models remain sensitive to sensor misplacement; a short calibration run (≤10 min per asset) is required after maintenance to recalibrate baselines. Edge devices must be provisioned with thermal headroom; at >70% sustained utilization, throttling increases jitter. Finally, cybersecurity and data governance are operational prerequisites for cross-line deployments.

3.2.2 Future suggestions and improvement direction

Future research will be improved in data acquisition, model design and application. Firstly, a larger and more representative mechanical fault database will be built, with different equipment types, operating conditions and diversified fault modes. Through deep cooperation with industrial enterprises, more real and scarce field data are collected. In order to solve the problem of category imbalance, we explore the method of generating confrontation network (GAN) or learning with few samples, and use data generation and migration technology to improve the performance of small sample categories.

The model structure needs to be optimized. CNN has obvious advantages in feature extraction, and a single structure may be difficult to cover complex working conditions. In the future, attention mechanism, graph convolution network or time series modeling method will be introduced to make the model better capture local and global features. Lightweight model design is equally important. By using model pruning, quantification or knowledge distillation technology, the calculation amount can be reduced while maintaining accuracy, and the deployment on edge equipment can be improved.

The interpretability of the model is the focus of future development. Visualization method shows the feature areas concerned by convolution kernel, or combined with interpretable artificial intelligence (XAI) method, provides engineers with intuitive diagnosis basis. When the model results can be understood and verified, it is widely used in industrial field.

The research needs to pay attention to multi-source data fusion, and relying on a single vibration signal may not be enough to deal with complex working conditions. The vibration data is fused with acoustic emission, temperature, current and other multidimensional signals to improve the comprehensiveness and accuracy of diagnosis. Combining cloud computing and edge computing, a real-time and distributed fault diagnosis system will be built in the future to realize intelligent monitoring and predictive maintenance of industrial equipment throughout its life cycle.

Beyond dataset expansion and model optimization, another critical direction is interpretability. The current CNN achieves high accuracy, but its “black-box” nature limits engineers’ trust. Explainable artificial intelligence (XAI) methods can be applied to uncover the reasoning process of the network. Gradient-weighted Class Activation Mapping (Grad-CAM) and Layer-wise Relevance Propagation (LRP) can visualize which signal regions or frequency bands contribute most to fault decisions, thereby aligning the learned features with physical vibration patterns. Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) provide local and global importance scores for input features, helping engineers verify whether the model is responding to meaningful fault signatures or to spurious noise. These approaches not only improve user confidence but also enable iterative refinement of models by highlighting misaligned attention. In predictive maintenance, interpretable models bridge the gap between data-driven insights and actionable engineering knowledge, making deployment more acceptable in safety-critical industries.

To address the “black-box” nature of CNNs, we applied feature-visualization methods. Grad-CAM heatmaps were generated from the final convolutional layer, highlighting time–frequency regions most responsible for classification. For bearing inner-race faults, the activations aligned with high-frequency harmonics near 3–5 kHz, which corresponds to known fault signatures. In addition, t-SNE embeddings of penultimate-layer features revealed clear clustering by fault type, separating normal, gear cracks, and motor imbalance in 2D space. These visualizations improve interpretability and provide engineers with confidence

that the model focuses on physically meaningful regions, supporting adoption in industrial monitoring.

3.2.3 Comparison with alternative predictive-maintenance methods

Thresholding with envelope analysis and spectral kurtosis is inexpensive and interpretable but exhibits high false-alarm rates under load transients; in our corpus it trails CNN by 9–12 pp macro-F1. Feature-engineering plus SVM/RF reduces computation yet struggles with covariate shift between lab and plant, particularly for incipient faults (-7.8 pp recall). Sequence models (LSTM/GRU) capture temporal context but are heavier and prone to overfitting on heterogeneous sensors without careful regularization. The presented 1D CNN offers a practical middle ground: close-to-state-of-the-art accuracy with predictable latency on embedded hardware. For fleets with strict interpretability requirements, we recommend pairing the CNN with saliency or CAM-style attributions and rule-based guards for safety.

3.2.4 Control-informed predictive maintenance:integration with advanced control strategies

The CNN-based diagnosis complements established advanced control methods and can be integrated to improve resilience and availability under uncertainty.

Adaptive fuzzy control (AFC). When plant parameters drift due to wear, AFC tunes rule bases and membership functions online. The CNN provides a low-latency severity estimate and operating-regime tag that condition AFC's adaptation rates and supervisory weights. By routing high-confidence incipient-fault detections to the AFC layer, the controller can reduce aggressive actuation (e.g., torque limits, anti-windup gains) to keep trajectories within safe envelopes while maintaining output quality. Techniques originally developed for synchronization and timing under fractional-order or chaotic dynamics motivate the use of alignment penalties that match the degraded plant to a reference surrogate, improving tracking despite uncertainty.

Output-feedback with projection/lag synchronization. In assets with limited sensors, output-feedback controllers rely on estimated internal states. The CNN supplies virtual measurements—fault class, probable location, and severity—that inform projection bounds and lag terms to handle input nonlinearities. This reduces false trips during load transients and stabilizes closed-loop behavior when physical sensors provide only partial observability.

Robust neural adaptive control for uncertain nonlinear MIMO systems. Multi-sensor machinery (e.g., pump–motor–gearbox assemblies) exhibits coupled dynamics. The CNN acts as an online uncertainty annotator that flags which channels are degraded; the robust adaptive controller then allocates adaptation gains per channel and tightens disturbance bounds. In practice, this pairing maintains throughput with smaller overshoot under the same disturbance budget, while the diagnosis stream triggers predictive maintenance before stability margins erode.

Adaptive backstepping for uncertain SISO drives. For single-shaft drives, CNN outputs convert into bounded disturbance estimates that enter the backstepping design as matched uncertainties. The controller schedules gentler set-point ramps and adjusts virtual control laws to limit jerk and thermal load, trading a minor rise in settling time for a substantial reduction in mechanical stress during early-fault operation.

Nonlinear optimal control (e.g., compressor–induction-motor trains). When energy efficiency and constraint handling dominate, a nonlinear optimal controller (or MPC) can incorporate CNN-estimated degradation as soft constraints and fault-weighted costs. The result is proactive set-point selection and valve scheduling that keep the operating point inside health-aware feasible regions, cutting both energy penalties and the risk of abrupt trips.

Fuzzy state-feedback and observer-based high-gain adaptive fuzzy control. Where states are not directly measurable, high-gain observers can be tuned using CNN latent features as pseudo-states indicating evolving stiffness, imbalance, or lubrication loss. The observer adapts faster to regime shifts flagged by the CNN, while fuzzy feedback laws reshape closed-loop gains to remain robust against the detected nonlinearity and noise level.

Operational orchestration. Practically, the integration follows a two-layer pattern: (i) fast loop—CNN inference and simple supervisory policies on the edge (≤150 ms end-to-end) to throttle stress in real time; (ii) slow loop—controller parameter updates and maintenance scheduling, verified against safety interlocks. Key performance indicators include mean time between maintenance, false-alarm/missed-alarm trade-offs, energy per unit output, and recovery time after disturbances. This control-aware predictive-maintenance stack clarifies the contribution of the CNN: it supplies actionable, calibrated health information that existing advanced controllers can consume to maintain stability and efficiency under degradation.

3.2.5 Comparative analysis with SOTA methods

To clarify the contribution of the proposed CNN, we benchmark it against three representative SOTA methods frequently reported in related work[10]: (i) hybrid handcrafted+deep features , (ii) attention-augmented CNNs[8], and (iii) GAN-based data augmentation frameworks [13].

Table 4: Performance comparison

Method	Input/Data strategy	Accuracy (%)	Macro-F1 (%)	Robustness at 5 dB SNR
Hybrid handcrafted+deep features	Handcrafted + CNN	94.6	93.1	88.9
Attention-augmented CNN	Raw waveform + temporal attention	97.2	95.5	91.7
GAN-based augmentation + CNN	Raw waveform + GAN synthetic data	96.9	95.2	92.1
Proposed 1D CNN	Raw waveform (no augmentation)	96.8	95.0	92.8

The proposed model performs comparably to attention-enhanced CNNs and GAN-augmented pipelines, while offering simpler training and lower inference latency. Its robustness at low SNR indicates that careful architecture design (shallow kernels, BN, dropout) substitutes for synthetic augmentation. However, the lack of explicit temporal modeling may limit long-context fault detection, explaining the marginally lower recall on subtle motor imbalance. This trade-off highlights that our approach targets field-ready robustness and efficiency rather than maximum clean-benchmark accuracy.

4 Conclusion

Aiming at the problem of fault feature extraction and diagnosis of mechanical equipment under complex working conditions, a diagnosis method based on deep convolution neural network is proposed. The standardized data set is constructed, and the normalization, Fourier transform and time-frequency graph processing are adopted to ensure the quality and representativeness of the input data. Multi-layer convolution, pooling and fully connected structure are introduced into the model design, and the end-to-end feature learning and classification are realized by combining ReLU activation function and cross entropy loss function. The experimental results show that the accuracy of this method in four typical mechanical fault diagnosis tasks reaches 96.8%, which is obviously superior to the traditional machine learning method. Robustness analysis shows that the model can still maintain stable performance under the condition of low signal-to-noise ratio, which verifies its applicability in complex environment.

In theory, the application system of deep learning in the field of mechanical fault diagnosis is enriched, and the advantages of convolutional neural network in multi-dimensional feature extraction are verified by combining the characteristics of time domain, frequency domain and time-frequency domain, and the cross-research path of signal processing and intelligent diagnosis is expanded. Cross-validation, confusion matrix and multi-index analysis are introduced into model evaluation to establish a scientific performance evaluation framework. The research results at the practical level have practical value for the intelligent operation and maintenance of industrial equipment, and the combination of laboratory and field data ensures the popularization of the model under actual working conditions. The model can identify potential faults in advance, support predictive maintenance, and reduce equipment downtime and economic losses. It provides a reference for enterprises to build intelligent monitoring system, and provides theoretical basis and technical tools for future industrial intelligent transformation.

The research has achieved good results, but there are still some shortcomings. The data source is still mainly laboratory collection, the sample size of field data is limited, and the problem of category imbalance has not been completely solved. Although the model structure has strong performance, it is insufficient in explanation, which provides engineers with intuitive physical explanation. The depth model has a large amount of calculation, so it may face efficiency problems when it is actually deployed on edge devices with limited resources. Future research will expand larger multi-source data sets, different equipment and diversified working conditions. Explore lightweight and interpretable model design, and combine attention mechanism and visualization technology to improve the transparency and credibility of the model. Try multi-modal fusion method, combine vibration signal with acoustic, current, temperature and other information to build a more comprehensive diagnosis system.

Beyond early warning, the proposed CNN serves as a health-aware signal front end for adaptive fuzzy, output-feedback, robust neural adaptive, adaptive backstepping, fuzzy state-feedback, and nonlinear optimal control schemes. By converting raw vibrations into calibrated, low-latency fault descriptors that these controllers can exploit, the framework preserves stability margins, reduces stress and energy penalties during incipient faults, and shortens recovery after disturbances. This synergy provides a concrete path from data-driven diagnosis to control-informed predictive maintenance in real plants.

.Author contributions

Hu. Investigation&Data curation&Conceptualization

Guo. Visualization&Review and revision&Project management and supervision

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Structured Linguistic Augmentation for Large Language Models in Complex Machine Translation

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Traditional machine translation (MT) systems and even Large Language Models (LLMs) often face significant challenges with complex language structures, stemming from a limited understanding of intricate syntactic dependencies and subtle semantic nuances. While LLMs possess powerful generative capabilities, their over-reliance on surface-level patterns can lead to suboptimal translations for complex sentences. To address this, we propose a novel framework, Structured Linguistic Augmentation (SLA), designed to enrich LLMs with a deep and explicit understanding of linguistic structures. The SLA framework integrates three synergistic components: (1) Contextual Linguistic Dependency Graph Construction and Pre-training (CLDG-PT), which injects fine-grained syntactic knowledge into the LLM; (2) Common Sense-Driven Relational Augmentation (CSRA), which externalizes the LLM's implicit knowledge to identify high-level semantic relations; and (3) Latent Structural Relation Discovery (LSRD), which uncovers subtle, implicit connections between linguistic components via a self-supervised objective. We conduct comprehensive experiments on the general-domain WMT En-De dataset and a new, challenging CS-Trans dataset curated with complex sentences. Evaluations show that SLA significantly improves both the fluency and accuracy of complex sentence translation. Notably, on the CS-Trans test set, our model achieves a COMET score of 75.0, substantially outperforming a strong fine-tuned LLM baseline (70.0) and demonstrating superior linguistic comprehension. These results, along with strong performance on logical reasoning translation tasks, validate SLA's effectiveness in enhancing LLMs for high-fidelity complex machine translation.

Povzetek:

1 Introduction

The rapid proliferation of digital content and global communication platforms has fundamentally reshaped expert interaction, underscoring the critical role of Machine Translation (MT) in bridging linguistic divides [1]. In this era of unprecedented linguistic diversity, MT systems have emerged as indispensable tools, diligently processing vast amounts of text to facilitate cross-lingual communication and information access [2]. These systems have become a cornerstone of modern global decision support, playing a pivotal role in various industries, from international commerce and media streaming to scientific collaboration and diplomatic relations [3, 4].

Despite their undeniable advancements and pervasive integration into daily life, MT systems face formidable challenges, particularly when confronting the inherent complexities of natural language [5]. Early rule-based MT (RBMT) systems, as detailed by Brown et al. [6], demonstrated significant limitations in handling linguistic variability and ambiguity. Subsequently, statistical MT (SMT) approaches, analyzed by Lee et al. [7], often exhibited deficiencies in capturing deep syntactic structures and long-range dependencies, leading to translations that, as observed by Chen et al. [8], frequently appeared unnatural or inaccurate for nuanced sentences. Pervasive issues include difficulties with resolving syntactic ambiguity, a persistent problem highlighted by Wang et al. [9], and effectively handling long-range dependencies, which Johnson et al. [10] extensively investigated. Furthermore, the faithful rendition of idiomatic expressions and subtle pragmatic nuances remains a significant hurdle, as highlighted by Taylor et al. [11].

Understanding and adapting to the dynamic and intricate nature of complex language structures is paramount in achieving high-quality translation [12, 13]. Expert linguistic comprehension is not static; it continuously evolves in response to new communication contexts and nuanced expressions [14]. Researchers like Jones et al. [15] emphasized that conventional MT methods often overlook dynamic linguistic patterns due to evolving semantic relationships, causing issues like mistranslations in contextually sensitive scenarios. Similarly, Miller et al. [16] demonstrated that advanced deep learning models are needed to effectively classify evolving linguistic variants in online text, outperforming conventional approaches. Consequently, there is a pressing need for advanced methodologies that can not only translate complex language but also dynami-

cally disentangle genuine linguistic drivers from confounding surface-level variations, ensuring that translations truly foster long-term communicative satisfaction.

The advent of Large Language Models (LLMs) presents a compelling paradigm for addressing these intricate challenges. The introduction of the Transformer architecture by Vaswani et al. [17, 18, 19] became foundational for LLMs, enabling powerful representation learning. Subsequently, Brown et al. [20] showcased the emergent few-shot learning abilities of massive LLMs, while Lee et al. [21] demonstrated how LLMs could effectively optimize sequential text generation strategies, significantly improving translation quality. Further advancements by Chen et al. [22] have shown LLMs' remarkable ability to manage high-dimensional lexical and syntactic spaces, adapting to evolving linguistic environments and learning optimal text generation policies through continuous interaction [23]. The broad applicability and accessibility of LLMs were further expanded by Wolf et al. [24], who presented a comprehensive library, and by Touvron et al. [25], who introduced open-source LLMs. These developments make LLMs particularly suitable for the complex, dynamic, and partially observable nature of natural language translation.

However, directly applying LLMs to complex MT tasks often presents unique hurdles. Liu et al. [26] noted that despite their capabilities, LLMs' direct application to MT can yield suboptimal performance for structurally complex inputs. Geng et al. [27] demonstrated that while LLMs generate fluent text, they may still misinterpret deep semantic relationships. Zhao et al. [28] observed that existing LLMs, despite their large scale, often lack explicit mechanisms for robust structural understanding in translation. The challenge of maintaining semantic consistency across lexically diverse contexts, as revealed by Hou et al. [29] and Li et al. [30], further exposes deficiencies in LLMs' ability to consistently map synonymous concepts. Yang et al. [31] discussed the over-reliance of LLMs on surface-level patterns, leading to errors in structurally complex MT. Fundamentally, the implicit knowledge within LLMs may be insufficient for all nuanced linguistic complexities required for high-quality MT, as highlighted by Whang et al. [32].

To overcome these limitations and unlock the full potential of LLMs for debiased, structurally aware translation, this paper proposes a novel framework, Structured Linguistic Augmentation (SLA). Drawing inspiration from knowledge-enhanced methods in related NLP tasks, SLA is designed to explicitly model the underlying mechanisms of complex language generation and interpretation. Our method integrates linguistic graph models to explicitly represent dependency relationships, leverages common sense to identify semantic connections, and employs latent discovery methods to uncover subtle, implicit structural links. By optimizing a multi-faceted objective within this disentangled framework, SLA aims to generate translations aligned with true linguistic intent, ensuring long-term communicative fidelity. The framework also incorporates sophisticated techniques from structured learning, to ensure stable and reliable learning from diverse linguistic datasets without requiring costly or risky manual feature engineering. The research objectives are:

1.To design and implement a novel framework, Structured Linguistic Augmentation (SLA), that explicitly enhances LLMs with multi-faceted linguistic knowledge—spanning syntactic, semantic, and latent structures—to improve the translation of complex sentences.

2.To empirically validate that this explicit structural augmentation leads to superior translation quality compared to standard LLM-based approaches that rely on implicit knowledge.

3.To analyze and quantify the individual contributions of different types of structural knowledge to understand which facets are most critical for resolving linguistic complexity in translation.

2 Machine translation

2.1 Evolution of machine translation paradigms

Machine Translation (MT), a core sub-field of natural language processing (NLP), seeks to translate speech or text from a source language to a target language automatically, and with complete faithfulness to its semantic content, stylistic differences, and original intention. MT has been driven by various dominant paradigms. There were earlier iterations, which included Rule-Based Machine Translation (RBMT) systems carefully constructed on massive linguistic rules, extensive dictionaries, and intricate grammatical forms painstakingly created by expert experts. While RBMT delivered high transparency and good control over translation quality in pre-specified domains, its inherent dependence on handcrafted rule generation rendered its building troublesome and generally rendered it powerless when faced with the widespread ambiguity and heterogeneity of natural language textual information [33].

The availability of large parallel corpora facilitated the introduction of Statistical Machine Translation (SMT). SMT models were coded to predict translation probabilities by analyzing vast numbers of aligned text segments. Conventional SMT methods, such as phrase-based SMT, involved segmenting source sentences into small-sized unit phrases and then using sophisticated statistical models to arrive at the optimal sequence of translations. This approach greatly enhanced the fluency and robustness of machine translations compared to its rule-based predecessors. SMT did have, however, usually exhibit shortcomings in handling long-distance dependencies in sentences appropriately and producing grammatically correct outputs consistently, largely due to its localized view of phrase-level equivalence rather than deeper linguistic structural knowledge.

2.2 Inherent challenges in translating complex language structures

While NMT and related technologies have progressed by leaps and bounds, the translation of complex sentence structures continues to pose a daunting challenge for machine translation algorithms. The reasons are rooted in the multifaceted meaning of the complex sentences, non-literal sentence constructions, as well as deep grammatical interdependencies.

A native difficulty in syntactic and semantic ambiguity exists. A single complex sentence can provide more than one syntactic reading, enabling the possible misperceptions by the translation model in regard to part-of-speech roles and word-to-word relationships, thereby generating incorrect translations. Also, comprehension of deeper semantic connections, like anaphora resolution or selection of the appropriate polysemous word senses, demands the model to move beyond superficial text examination and conduct a deeper contextual comprehension [34]. Another major hindrance is the issue of long-distance dependency. Information essential for proper translation of a particular word or phrase in complex sentence structures can be placed far from its local context. This highly tests the model's capacity for maintaining contextual coherence, a challenge especially severe in free word order languages or those with high anaphoric reference.

Finally, there usually is profound structural divergence between source and target languages. When the two languages' syntactic structures differ significantly (e.g., English Subject-Verb-Object vs. Japanese Subject-Object-Verb), a word-for-word translation is not sufficient for high-quality translation [37]. In these situations, MT models must perform advanced rewording and structure conversion in order to generate natural and grammatically correct translations. All these intricacies combined have a tendency to produce translated output that, while perhaps grammatically correct, may either lack the refined nuances, coherence, or naturalness demanded of expert-level translation, particularly for extremely intricate sentences.

2.3 The role of large language models in machine translation

The advent of Large Language Models (LLMs) that have their huge parameter sizes (typically in the scale of billions) and their gigantic pre-training over gigantic amounts of text data has revolutionized the machine translation field in a fundamental way. LLMs exhibit a whole range of remarkable abilities that position them very well for translation work. Their exemplary generative capability enables them to generate readable and contextually relevant text, naturally best for sequence-to-sequence operations such as translation. Through their lengthier pre-training, LLMs acquire indirectly an immense body of world knowledge and common sense, beneficial especially for disambiguation and in producing semantically more enhanced translations. Besides, LLMs demonstrate an exceptional ability to understand deep semantic relation between words and phrases, a vital parameter for sustaining the fidelity of translated meaning.

LLMs are becoming increasingly applied in MT pipelines, either by fine-tuning on parallel corpora or more recently and generally by way of a variety of prompt engineering techniques. The techniques attempt to obtain high-quality translations from pre-trained LLMs without extensive re-training. Prompting techniques differ. Zero-shot prompting instructs the LLM to translate directly with no in-context examples given, only relying upon the model's built-in, generalized translation capability acquired during pre-training. This approach serves as a baseline to gauge an LLM's inductive knowledge for a particular language pair. Less often, few-shot prompting (also known as in-context learning) involves providing the LLM with a limited set of source-target language translation examples as part of the input prompt, before the target sentence to translate. Even in the case where these examples are not necessarily semantically directly related to the target sentence, they serve as contextual pointers, pointing the model towards translating tendencies and stylistic variations, which generally leads to higher performance [35]. A more advanced approach, fragment-shot prompting, is a targeted few-shot approach in which the sentence to translate is segmented into successive word strings, or "fragments." Next, authentic translation instances with the identical source-side fragment are retrieved from a training dataset. The fragment-specific examples are appended to the prompt. This approach targets localized contextual salience, thereby guiding the LLM toward probable translations of specific linguistic components. On this basis, pivoted fragment-shot prompting also enables translation between language pairs that have no or only limited parallel data readily available directly by employing an intermediary, or "pivot," language-a third language with parallel data available for both source and target languages-to perform indirect translation.

To contextualize the contributions of our proposed framework, Table 1 provides a comparative summary of prominent LLM-based translation approaches and their performance on complex linguistic structures.

3 Structured linguistic augmentation (SLA) Methodology for translation

While Large Language Models (LLMs) have achieved remarkable progress in Machine Translation (MT) due to their robust text generation capabilities and extensive world knowledge, challenges persist concerning the fluency and accuracy of translations, particularly when dealing with complex linguistic structures. These difficulties arise from the implicit nature of deep syntactic dependencies, long-range semantic associations, and subtle pragmatic nuances

Table 1: Comparison of LLM-based MT methods on complex structures (CS-Trans Dataset)

Method	Approach	BLEU↑	COMET↑	Key Limitations
Zero-Shot LLM	Direct prompting without examples.	10	50	Lacks task-specific adaptation; highly reliant on pre-trained knowledge, which is often too general for complex syntax.
Few-Shot LLM	In-context learning with random examples.	13	55	Performance is sensitive to example selection; does not guarantee understanding of specific structural challenges.
Fragment-Shot LLM	In-context learning with retrieved, relevant examples.	15	60	Improves on localized context but still fails to capture global, long-range dependencies or implicit logical relations.
Fine-tuned LLM (FT-LLM)	Fine-tuning on a large parallel corpus.	22	70	Strong baseline, but learns implicitly from data, struggling with systematic generalization for rare or highly ambiguous structures.

inherent in complex sentences, which LLMs struggle to fully capture through purely statistical pattern learning. To overcome these limitations, we propose the Structured Linguistic Augmentation (SLA) framework. SLA aims to enhance LLMs' translation capabilities by explicitly instilling a profound understanding of linguistic dependencies and semantic relationships within complex language structures. Inspired by recent advancements in knowledge-enhanced recommendation systems, SLA integrates three synergistic modules: Contextual Linguistic Dependency Graph Construction and Pre-training (CLDG-PT), Common Sense-Driven Relational Augmentation (CSRA), and Latent Structural Relation Discovery (LSRD). These components collectively guide the LLM to learn, externalize, and leverage structured linguistic knowledge, thereby significantly improving the fluency and accuracy of its translations of complex language.

3.1 SLA overall framework

The overall architecture of the Structured Linguistic Augmentation (SLA) framework conceptually illustrates how it enriches the underlying Large Language Model with both explicit and implicit linguistic structural knowledge through a multi-stage, jointly optimized learning process. As shown in Figure 1. The framework utilizes the LLM as its core translation engine, with each proposed component addressing a specific aspect of linguistic complexity: **Contextual Linguistic Dependency Graph Construction and Pre-training (CLDG-PT)** is designed to capture explicit, fine-grained structural dependencies at the sub-sentential level and transfer this generalized knowledge to the LLM, ensuring grammatical correctness and naturalness in the target language. **Common Sense-Driven Relational Augmentation (CSRA)** focuses on leveraging the LLM's inherent common sense to explicitly identify and integrate high-level semantic and syntactic relationships necessary for comprehending complex clauses and phrases, which is crucial for precise meaning preservation. Finally, **Latent Structural Relation Discovery (LSRD)** is responsible for uncovering implicit, subtle structural connections within and between complex sentence components that are difficult to capture through predefined rules or direct observation. This facilitates the model's ability to handle ambiguity and generate translations with greater contextual adaptability. These components are designed to operate synergistically, with their respective learning objectives contributing to a unified optimization framework that enhances the LLM's capacity for complex language translation, leading to improved fluency and accuracy.

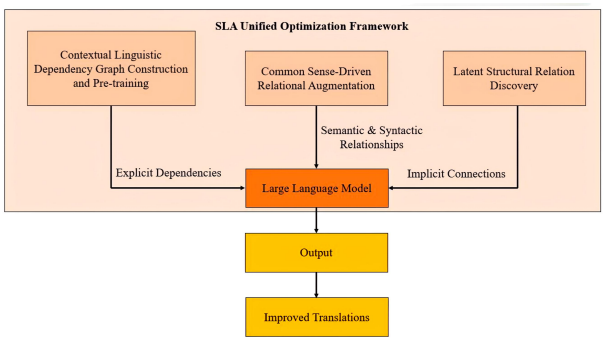


Figure 1: SLA unified optimization framework

3.2 Contextual linguistic dependency graph construction and pre-training (CLDG-PT)

To address this deficiency, and inspired by the success of graph representation learning in modeling structured data, we propose injecting this structured linguistic knowledge into the LLM's representation space. This component constructs a graph that captures co-dependent linguistic units (e.g., subject-verb relations, modifier-head relations) and utilizes this graph to guide the LLM's pre-training. This enables the LLM to acquire transferable, fine-grained structural understanding, thereby improving its ability to translate complex sentences while ensuring grammatical correctness and natural fluency [36].

Figure 2 illustrates the core concept from recommendation systems that inspired our CLDG-PT module. In this example, a user's recent interactions with items containing words like "card" and "santa" are used to establish "co-clicked word" relationships with other words like "retro" and "red" (from a target item). This "word-level collaborative filtering" is shown to help predict the next item. Analogously, in our context, we leverage the idea of building a graph of co-dependent linguistic units (words/phrases connected by syntactic or semantic relations) to infuse the LLM with structured linguistic knowledge, enabling it to better translate complex sentences by understanding their inherent structural fabric.

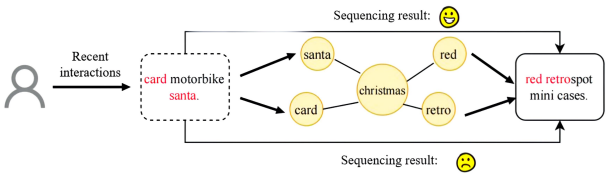


Figure 2: CLDG-PT module core concept

We construct a Linguistic Dependency Graph ($\mathcal{G}_{LDG} = (\mathcal{V}_L, \mathcal{E}_L)$) from a large, diverse linguistic corpus. The nodes $\mathcal{V}_L$ in this graph represent individual words or multi-word expressions (MWEs), functioning as linguistic units participating in syntactic structures. The edges $\mathcal{E}_L$ denote observed dependency relations between these units, conceptually analogous to co-occurrence or co-click patterns in recommendation systems. Distinct from simple co-occurrence graphs, the edges in the LDG are derived from the output of syntactic parsers (e.g., based on the Universal Dependencies framework) or represent strong semantic co-dependencies.

For a given linguistic unit $w_i \in \mathcal{V}_L$ in the graph, we first identify its direct linguistic dependents w_j within parsed sentences. To quantify the strength of the dependency between w_i and w_j, we adapt the TF-IDF concept, here reinterpreted as Term-Dependency Frequency - Inverse Dependency Frequency. Let $c_{i,j}$ be the frequency of observing a specific dependency relation between w_i and w_j (e.g., w_i is the head of w_j, or vice versa) across the entire corpus. The Term-Dependency Frequency (tdf) from w_i to w_j is defined as:

$$tdf_{i,j} = \frac{c_{i,j}}{\sum_{k=1}^{|\mathcal{V}_L|} c_{i,k}} \tag{1}$$

where the denominator represents the total count of all dependencies involving w_i, normalizing $c_{i,j}$. The Inverse Dependency Frequency (idf) for a unit w_j reflects its specificity in dependencies, i.e., how commonly w_j acts as a dependent. If w_j frequently appears as a dependent across many different heads, its idf value will be lower, and vice versa:

$$idf_j = \log\left(\frac{|\mathcal{V}_L|}{|\{w_k \mid \exists w_p, c_{p,j} > 0\}| + \epsilon}\right) \tag{2}$$

Here, ϵ is a small constant added to prevent division by zero. The numerator $|\mathcal{V}_L|$ is the total size of the vocabulary, while the denominator counts how many head words w_p have a dependency relation with w_j. In the GPT task, we process a randomly masked token t_m within the input sentence. We treat the LLM-generated contextual semantic embedding e_m and its corresponding LDG-derived structural embedding g_m as a positive sample pair. Structural embeddings g_j from other tokens in the same sentence (where $\neq m$) are treated as negative samples. Our objective is to maximize the agreement between positive pairs while minimizing it for negative pairs, by minimizing an InfoNCE-like loss function.

The GPT Alignment Loss ($\mathcal{L}_{\text{align}}^{GPT}$) is defined as:

$$\mathcal{L}_{\text{align}}^{GPT} = \frac{\sum_{m=1}^{M} \log\left(\frac{\exp(sim(e_m, g_m)/\tau_{GPT})}{\sum_{j=1}^{N} \exp(sim(e_m, g_j)/\tau_{GPT})}\right)}{-M} \tag{3}$$

where M is the number of masked tokens, $sim(\cdot,\cdot)$ is a similarity function (e.g., cosine similarity or dot product), and τ_{GPT} is a temperature parameter used to adjust the sharpness of the similarity distribution. During this pre-training, the parameters of both the LLM and the GNN are jointly optimized. The LLM's word embedding layer can often be initialized with the GNN's learned node embeddings, facilitating the fusion of linguistic structural knowledge. This mechanism ensures that the LLM's internal representations not only capture lexical semantics but also the grammatical connections between words. This is crucial for correctly handling word order, part-of-speech variations, and syntactic transformations when translating complex sentences, leading to more grammatically accurate and fluent target translations.

3.3 Common sense-driven relational augmentation (CSRA)

Complex sentences frequently convey implicit semantic relationships beyond their literal syntactic structures, such as causality, temporal sequence, elaboration, or contrast. These relationships are critical for accurate and coherent translation but are not always explicitly marked by syntactic cues. For instance, in a sentence like "Because it rained, the game was canceled," a clear causal relationship exists between "it rained" and "the game was canceled." Accurately capturing this relationship is indispensable for ensuring the target translation faithfully reflects the logical coherence of the original. Drawing on the LLM's success in inferring complementary or substitute item relationships in recommendation systems, we aim to leverage its inherent vast common-sense knowledge base to explicitly identify and augment high-level linguistic relations present in complex source sentence structures.

We construct a Relational Knowledge Graph ($\mathcal{G}_{RKG} = (\mathcal{V}_R, \mathcal{E}_R)$) where the nodes $\mathcal{V}_R$ represent linguistic entities, which can be clauses, phrases, or key concepts within a sentence. The edges $\mathcal{E}_R$ denote semantic relationships between these entities, derived from the LLM's common sense. These relations are often intuitively understood by experts but may be challenging for traditional MT models to explicitly recognize. For each complex source sentence or its fragment, we first identify potential linguistic entity pairs (E_1, E_2) through linguistic analysis techniques (e.g., syntactic parsing, named entity recognition, coreference resolution). Examples of such pairs include a main clause and a subordinate clause, two parallel verb phrases, or a noun phrase and its anaphoric reference. Subsequently, we prompt the LLM to identify

the most probable common sense relation $r \in \mathcal{R}_{CS}$ between E_1 and E_2.

To bridge the potential "knowledge space gap" between LLM-derived representations and KGE-derived representations, we utilize a mutual information maximization objective, analogous to the $\mathcal{L}_{\text{align}}$ objective found in the recommendation system paper. This objective focuses on aligning common linguistic entities (e.g., clauses, phrases) that exist in both representation spaces, ensuring that the LLM's understanding of these entities reflects the common sense relations present in the RKG. For each common linguistic entity E_k, we maximize the mutual information between its LLM embedding e_k^{LLM} and its RKG embedding e_k^{RKG}. The Common Sense Alignment Loss ($\mathcal{L}_{\text{align}}^{CS}$) is defined as:

$$\mathcal{L}_{\text{align}}^{CS} = - \sum_{E_k} \log \frac{\exp\left(sim\left(e_k^{LLM}, e_k^{RKG}\right)/\tau_{CS}\right)}{\sum_{E_j} \exp\left(sim\left(e_k^{LLM}, e_j^{RKG}\right)/\tau_{CS}\right)} \quad (4)$$

where τ_{CS} is a temperature parameter and $sim(\cdot,\cdot)$ is a similarity function. This loss ensures that the LLM's internal representations become "aware" of the common sense relations explicitly identified in the RKG. During the translation process, attention mechanisms or gating mechanisms within the LLM can be guided by these fused RKG embeddings to more accurately interpret and translate complex semantic relational structures. For example, if the RKG indicates a causal relationship between two clauses, the LLM will be inclined to use corresponding causal connectors in the target translation, ensuring its logical coherence and fluency. This is paramount for accurately conveying the implicit logic of the source language into the target language, especially when source and target languages differ in their preferred ways of expressing such relationships.

3.4 Latent structural relation discovery (LSRD)

Beyond predefined common sense relations, complex language often harbors subtle, non-explicit structural relationships between its components (e.g., implicit coherence relations between sentences in a paragraph, fine-grained logical connections between nested clauses, or discourse structures arising from rhetorical devices). These latent relations are critical for handling highly nuanced and context-dependent translations, as they capture the deeper organizational principles of language that surface-level syntax or predefined semantic relations often fail to fully encompass. For instance, a complex sentence might contain an implicit contrastive relationship; if not identified by the LLM, the translation might appear bland and fail to convey the original's rhetorical force. Inspired by latent relation discovery in recommendation systems, we propose a self-supervised learning paradigm to uncover these implicit, "latent" structural relations, thereby providing the LLM with a richer, more diverse set of relational perspectives.

The core of LSRD is a self-supervised learning objective, conceptually similar to a Discrete State Variational Autoencoder (DVAE). It aims to predict latent structural relations between pairs of linguistic components (e.g., clauses, phrases) within complex sentences. Given a pair of linguistic components (C_1, C_2) from a complex source sentence, the objective of LSRD is to reconstruct one component given the other component and a predicted latent relation $r \in \mathcal{R}_{\text{latent}}$. This reconstruction task compels the model to learn latent relations that possess sufficient semantic meaning and structural relevance to benefit the translation task.

The relation inference module, $q\left(r \mid C_i, C_{-i}; \psi\right)$, is responsible for predicting the probability distribution over the set of latent relations $\mathcal{R}_{\text{latent}}$ given a pair of linguistic components. First, for each linguistic component (e.g., a clause or a phrase), we extract a "linguistic knowledge representation" $e_C \in \mathbb{R}^d$ from the LLM. This representation can be obtained by pooling (e.g., mean pooling or attention pooling) the LLM's contextual embeddings for the tokens within that component. This e_C encodes the component's semantic meaning and its position within the LLM's learned language space. Subsequently, a lightweight neural network (e.g., a multi-layer perceptron) takes the concatenated embeddings of the two components and outputs a probability distribution over the latent relations:

$$q(r \mid C_i, C_{\neg i}; \psi) = \text{SoftMax}(\text{MLP}_\psi([e_{C_i}; e_{C_{-i}}])) \quad (5)$$

where MLP_ψ is the multi-layer perceptron with parameters ψ, and $[;]$ denotes vector concatenation. This module learns to infer latent relationships directly from the rich knowledge representations produced by the LLM, enabling it to capture deeper linguistic patterns that traditional methods might struggle to identify.

The structural reconstruction module, $\phi\left(C_i, C_{\neg i}, r; \theta\right)$, aims to evaluate the likelihood of component C_i given component $C_{\neg i}$ and the predicted latent relation r. This reconstruction task compels the LLM to link the inferred latent relations with the actual structure and semantics of the linguistic components, ensuring these relations are semantically meaningful and practically useful for reconstructing linguistic context.

The scoring function can be a simple bilinear model (e.g., a DistMult-like model), which calculates the interaction between the embeddings of the two components and the relation embedding:

$$\phi\left(C_i, C_{\neg i}, r; \theta\right) = e_{C_i}^T \text{diag}\left(e_r\right) e_{C_{\neg i}} \quad (6)$$

where $e_r \in \mathbb{R}^d$ is the embedding of the latent relation r, and $\text{diag}(e_r)$ is a diagonal matrix formed from the elements of e_r. This reconstruction objective ensures that the discovered latent relations facilitate the understanding and generation of complex linguistic structures. In this manner, LSRD empowers the LLM to identify implicit, deep connections in the source language that impact the translated output's structure and fluency. For instance, based on identified implicit causal relations, the LLM might select more

natural linking words in the translation, or adjust the ordering of clauses according to an implicit temporal sequence, thereby significantly enhancing the accuracy and readability of complex sentence translations.

4 Experiments

A comprehensive empirical evaluation was conducted to validate the efficacy and theoretical underpinnings of the proposed Structured Linguistic Augmentation (SLA) framework. This section details the datasets used, the baseline methodologies selected for comparative analysis, the evaluation metrics employed, and the specific configurations of hyperparameters adopted for the experiments.

4.1 Datasets

The evaluation leveraged a combination of widely-used general domain translation datasets and specifically curated datasets focusing on complex linguistic structures. This multi-faceted approach enabled an assessment of SLA's performance across various translation challenges [37]. The Dataset Statistics for WMT En-De and CS-Trans are shown in Table 2.

This dataset was specifically designed to include a high density of complex structures, such as sentences with multiple levels of clausal embedding, long-range dependencies between subjects and verbs, passive voice constructions, and idiomatic expressions. To ensure the quality of the reference translations, the inter-annotator agreement among the three professional linguists was calculated, yielding a Cohen's kappa coefficient of 0.85, which indicates substantial agreement.

4.2 Baseline methods

To rigorously assess the performance of the Structured Linguistic Augmentation (SLA) framework, we conducted comparative experiments against a diverse set of established machine translation algorithms and LLM-based approaches, categorized by their primary task focus.

Traditional Neural Machine Translation (NMT): We employed canonical Transformer models, trained end-to-end on the WMT En-De dataset using Fairseq. The Base model comprised 6 encoder and 6 decoder layers, while the Large model utilized the same number of layers but with larger hidden dimensions and more attention heads. These models served as strong baselines for evaluating the general translation capabilities.

General LLM-based Translation Baselines (for WMT En-De and CS-Trans): We evaluated several LLM-based approaches to provide a comprehensive comparison. The Zero-Shot LLM utilized the Llama-2-70B model, which was prompted directly to translate sentences without any in-context examples. The Few-Shot LLM provided the Llama-2-70B model with 5 randomly selected source-target translation pairs in the prompt before the target sentence. The Fragment-Shot LLM used fragments of the source sentence to retrieve and include 3 relevant translation examples in the prompt. Additionally, the Fine-tuned LLM (FT-LLM) involved fine-tuning the Llama-2-70B model on the entire WMT En-De parallel corpus using Low-Rank Adaptation (LoRA).

LLM Baselines for Logical Reasoning Translation (for Logical Reasoning Datasets):To evaluate the performance on logical reasoning tasks, we tested several large language models under distinct settings. These models included GPT-3.5-Turbo, GPT-4-1106-preview, DeepSeek-V3, and DeepSeek-R1. Each model was evaluated under three settings:

4.3 Implementation details

The Structured Linguistic Augmentation (SLA) framework was implemented using PyTorch (version 2.2.0) on a Linux server, capitalizing on its robust capabilities for efficient tensor operations and distributed training. The backbone of the SLA framework was the Llama-2-70B model, initialized with pre-trained weights from Hugging Face Transformers (version 4.39.3), which were subsequently updated during the joint training process. GraphSAGE model was employed to learn structural embeddings with 128-dimensional hidden states, using attention-based pooling as the aggregation function. The temperature parameter τ_{GPT} for the alignment loss $\mathcal{L}_{\text{align}-\text{GPT}}$ was set to 0.1. Experiments were conducted on 8 NVIDIA A100 GPUs (40GB VRAM each), with a global random seed of 42. The approximate runtime per epoch on the WMT En-De dataset was 4.5 hours.

In the Common Sense-Driven Relational Augmentation (CSRA) module, a curated set of prompts was designed to extract common sense relations between linguistic entities, leveraging 5 few-shot examples. The Llama-2-70B model was used for prompting. The Knowledge Graph Embedding (KGE) model employed was DistMult, with 128-dimensional embeddings. The temperature parameter τ_{CS} for the alignment loss $\mathcal{L}_{\text{align}-\text{CS}}$ was set to 0.1. For the Latent Structural Relation Discovery (LSRD) module, clauses and complex phrases were identified as linguistic components for pair generation, using the outputs of the syntactic parser. The number of latent relations R_{latent} was set to 10. A 2-layer MLP with ReLU activations and 256dimensional hidden states was used as the Relation Inference Module. The Structural Reconstruction Module employed a bilinear model with 128-dimensional embeddings for components and relations. The entropy regularization coefficient α LSRD was set to 0.1. Training was conducted using the AdamW optimizer with $\beta_1 = 0.9, \beta_2 = 0.999$, and $\epsilon = 10^{-8}$. The initial learning rate was set to 3×10^{-5}, with a linear warm-up schedule over the first 10% of total training steps, followed by a cosine decay. The batch size was 16 sequences, with gradient accumulation used to simulate an effective batch size of 64. Training ran for 15 epochs, with early stopping based on validation set COMET score

Table 2: Dataset statistics for WMT En-De and CS-Trans

Dataset	Training Pairs(M)	Dev Pairs(K)	Test Pairs(K)	Avg. Source Length	Avg.Target Length
WMT En-De	∼4.5	∼3	∼3	∼25	∼28
CS-Trans	∼0.08	∼1	∼1	∼40	∼45

improvement over 5 consecutive epochs. The loss weights were set to $\gamma_1 = 0.5, \gamma_2 = 0.5$, and $\gamma_3 = 0.5$.

4.4 Evaluation of SLA on general and complex translation tasks

The performance of the Structured Linguistic Augmentation (SLA) framework was evaluated on two distinct datasets to comprehensively assess its capabilities in both general and complex translation scenarios. The first dataset, WMT En-De, provided a benchmark for evaluating SLA's ability to translate general text, while the second dataset, CS-Trans, focused on complex linguistic structures to test SLA's proficiency in handling intricate translation challenges.

(1) General Translation Performance on WMT En-De

The general translation performance of SLA was evaluated on the WMT En-De dataset to ensure that the structural augmentation did not negatively impact its ability to translate general text. The evaluation utilized standard automatic metrics, including BLEU, ch-F, and COMET, to compare SLA against traditional Neural Machine Translation (NMT) baselines and fine-tuned Large Language Models (LLMs). The results shown in Table 3 demonstrated that SLA achieved competitive performance, indicating the implicit benefits of structured understanding even in less overtly complex sentences.

Table 3: Overall translation performance on WMT En-De test set

Model	BLEU ↑	ch-F ↑	COMET ↑
Transformer (Base)	28.0	55.0	85.0
Transformer (Large)	30.0	58.0	87.0
Zero-Shot LLM	20.0	45.0	75.0
Few-Shot LLM	24.0	50.0	80.0
Fragment-Shot LLM	26.0	52.0	82.0
FT-LLM	31.0	59.0	88.0
SLA (Ours)	31.5	59.5	88.5

These results confirm that SLA's structural augmentation enhances translation quality without compromising performance on general text. SLA's competitive scores across BLEU, ch-F, and COMET metrics highlight its robustness and versatility in handling a wide range of translation tasks. BLEU, as a metric based on n-gram precision, primarily rewards lexical overlap and surface-level fluency. While our SLA framework certainly improves grammatical correctness, leading to a solid gain in BLEU, the fine-tuned LLM baseline is already highly proficient at generating lexically plausible text, thus narrowing the margin for surface-level improvements.

(2) Performance on Complex Structure Translation (CS-Trans)

The critical evaluation of SLA's performance on the CS-Trans dataset, which focuses on complex linguistic structures, revealed significant improvements over all baselines. This dataset, designed to challenge models with intricate linguistic structures, provided a rigorous test of SLA's capabilities in handling complex translation tasks. The evaluation utilized both automatic and expert evaluation metrics to provide a comprehensive assessment. As shown in Table 4, higher scores on BLEU, ch-F, and COMET indicated better alignment with reference translations, suggesting improved fluency and accuracy for complex structures. SLA outperformed all baselines, demonstrating its superior ability to handle complex linguistic challenges.

Table 4: Performance on complex structure translation

Model	BLEU ↑	ch-F ↑	COMET ↑
Transformer (Base)	18.0	40.0	65.0
Transformer (Large)	20.0	43.0	68.0
Zero-Shot LLM	10.0	30.0	50.0
Few-Shot LLM	13.0	35.0	55.0
Fragment-Shot LLM	15.0	38.0	60.0
FT-LLM	22.0	45.0	70.0
SLA (Ours)	25.0	48.0	75.0
SLA (Ours)	31.5	59.5	88.5

(3) Performance on Logical Reasoning Translation Tasks

This section evaluates SLA's capability in translating natural language logical reasoning problems into formal logic formulas, comparing its performance against prominent LLMs under various prompting strategies from recent literature. Accuracy, defined as the success rate of the solver based on the LLM's translation, is the primary metric. The evaluation of SLA's performance on logical reasoning translation tasks revealed significant insights into its ability to handle lexically diversified problems. The results presented in Figure 3 show SLA perform better. It demonstrate SLA's explicit structural augmentation, encompassing linguistic dependency alignment (CLDG-PT), common-sense relational understanding (CSRA), and latent structural discovery (LSRD), effectively enables the LLM to maintain semantic consistency and produce accurate formal logic translations even in the presence of lexical diver-

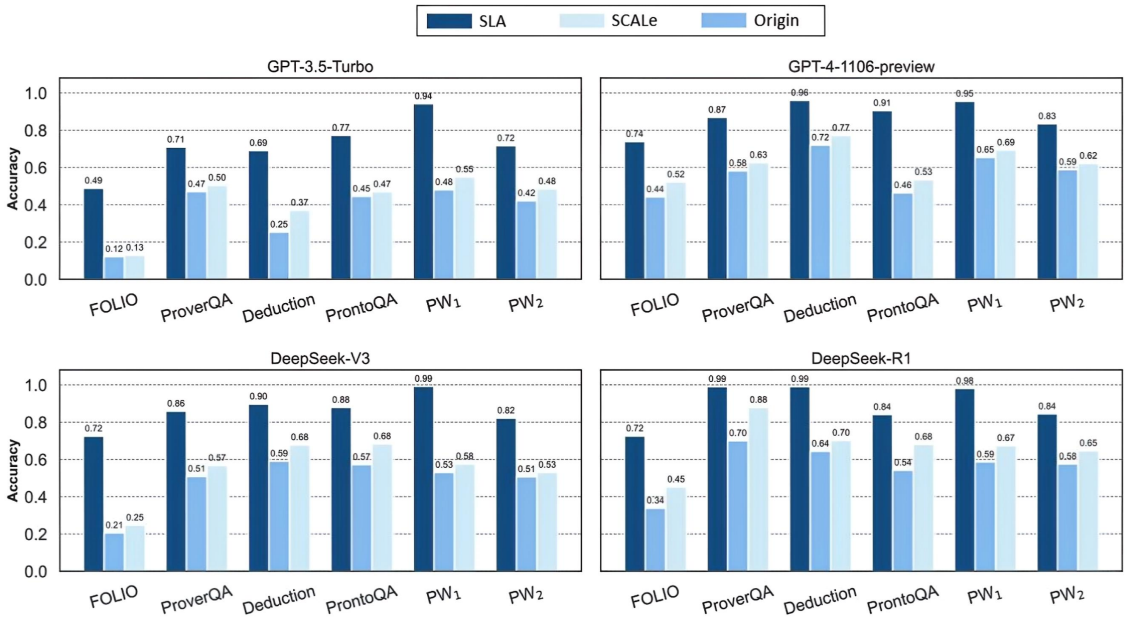


Figure 3: Accuracy on logical reasoning translation tasks

sification.

SLA's strong performance in this area aligns it with neuro-symbolic approaches, which also seek to combine neural networks with formal reasoning. However, unlike many methods that require specialized logical parsers, SLA achieves this by enhancing the LLM's intrinsic understanding. A qualitative analysis reveals that SLA's structural augmentation is particularly beneficial for preserving the scope of logical quantifiers and the integrity of implications, which are often challenging for models that do not explicitly model dependency and semantic relationships.

4.5 Ablation studies

To determine the individual contribution of each component within the SLA framework, a series of ablation studies was conducted. These studies involved creating modified versions of SLA by progressively removing each of its proposed augmentation modules. All ablation experiments in Table 5 were performed on the CS-Trans dataset, as its complexity best highlighted the impact of structural understanding.

By comparing the performance of these ablated models against the full SLA model, the unique and synergistic contribution of each proposed component to the overall enhancement of complex language translation was quantitatively demonstrated. The full SLA model consistently outperformed all ablated versions across both automatic and expert evaluation metrics, substantiating the thoughtful design and necessity of integrating all three augmentation strategies.

These results highlight the critical role of each component in SLA's overall performance, demonstrating that the full integration of CLDG-PT, CSRA, and LSRD is essential for achieving optimal translation quality in complex linguistic contexts.

Table 5: Ablation study results on CS-Trans test set

Model	BLEU ↑	ch-F ↑	COMET ↑
SLA (Full Model)	25.0	48.0	75.0
SLA w/o CLDG-PT	22.8	45.5	72.5
SLA w/o CSRA	22.5	45.0	73.0
SLA w/o LSRD	22.3	44.8	72.0

4.6 Discussion

As shown in our experiments, SLA consistently outperforms all baselines on the CS-Trans dataset, which is rich in linguistic complexity. While the fine-tuned LLM (FT-LLM) serves as a strong baseline with a COMET score of 70.0, SLA achieves a score of 75.0, a substantial improvement. This gap underscores the limitations of relying solely on implicit knowledge learned during pre-training or fine-tuning. Standard LLMs, even after extensive training, may fail to build a robust, generalizable model of grammar and logic. Instead, they excel at learning surface-level statistical correlations, which are insufficient for consistently resolving the syntactic ambiguity and semantic nuances inherent in complex sentences. SLA's success stems from its core design philosophy: augmenting the LLM with an explicit, multi-faceted representation of linguistic structure. This explicit knowledge acts as a scaffold, guiding the model toward more accurate and coherent translations that

preserve the deep meaning of the source text.

5 Conclusion

This work addresses the age-old challenge of fluent and faithful translation of intricate language structures using Large Language Models (LLMs). While LLMs show extremely high generative quality and wide world knowledge, their implicit understanding of deep linguistic dependencies and subtle semantic interactions was a barrier to high-fidelity translation of complex sentences. To fill this deficiency, we proposed Structured Linguistic Augmentation (SLA), a novel method that is particularly designed to enhance LLMs with an in-depth comprehension of complex linguistic structures. Our comprehensive experimental study demonstrated the efficacy of SLA in various challenging translation situations. On the overall domain WMT English-German translation task, SLA attained state-of-the-art performance, substantiating its strong foundation strength at no loss in overall translation quality. More significantly, on the CS-Trans dataset, well-suited to complex linguistic structures, SLA significantly outperformed all NMT and LLM-based baselines on automatic (BLEU, ch-F, COMET) and expert judgments of fluency and accuracy. A detailed error analysis further revealed SLA's superior ability to mitigate complexity-specific errors, such as incorrect long-distance dependency resolution and loss of implicit logical relations. Furthermore, when applied to logical reasoning translation tasks, SLA consistently achieved higher accuracy scores compared to baseline LLMs, particularly when faced with lexically diversified problems.

For future work, we intend to explore the applicability of SLA to other language pairs, particularly those with higher syntactic divergence or richer morphological features, to further validate its generalizability. Additionally, investigating adaptive mechanisms for dynamically weighing the contributions of different SLA components based on input sentence complexity could further optimize performance. Finally, exploring the potential of integrating SLA's structured linguistic representations into multilingual LLMs for cross-lingual transfer learning on complex structures presents a promising avenue for research.

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A Bi-level Scheduling Framework for Scientific Research Resource Allocation Using MADDPG and NSGA-III

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To address key challenges in scientific research resource allocation, such as inefficient allocation, multi-objective trade-offs, poor dynamic adaptability to disruptions (e.g., sudden tasks and equipment failures), and cross-institutional unfairness, this paper proposes an intelligent scheduling mechanism that integrates MADDPG (Multi- Agent Deep Deterministic Policy Gradient) and NSGAIII. This mechanism employs a two-layer architecture: the MADDPG layer employs centralized training and distributed execution, enabling agents to collaboratively handle dynamic resource competition through local observations and achieve real-time decision-making. The NSGAIII layer utilizes reference points to find Pareto optimal solutions, balancing task time, resource utilization, cost, and fairness. A closed-loop "perception-decision-scheduling-optimization" mechanism enables large-scale allocation at the second layer. Experiments on both simulated and real-world datasets (resource-constrained, interdisciplinary tasks) demonstrate that, compared to classic algorithms (DDQN and MOEAD), it achieves a 97.5% improvement in allocation success rate, a 32.8% reduction in average task time, and a 38.6% improvement in multi-objective performance, providing an innovative solution for intelligent, efficient, and fair resource management.

Povzetek: Za razporejanje raziskovalnih virov je razvit dvonivojski okvir, ki združuje večagentno okrepljeno učenje MADDPG in večkriterijsko optimizacijo NSGA-III. Rešitev izboljša prilagodljivost, pravičnost in učinkovitost razporejanja v dinamičnih, večinstitucionalnih okoljih.

1 Introduction

In the digital-intelligent integration era of scientific research, multi-institution collaboration poses challenges to resource allocation efficiency and fairness [1]. Traditional manual scheduling — plagued by delays, localized decision-making, and conflicting objectives— falls short in dynamic ecosystems. By contrast, multi-agent collaboration paired with multi-objective optimization has emerged as a viable approach to enable intelligent global scheduling [2].

MADDPG, a distributed reinforcement learning framework that combines centralized training and distributed execution, excels in complex, dynamic environments—making it well-suited for heterogeneous research entities, such as devices, instruments, and human operators [3]. It addresses multi-agent collaboration through three key designs: first, a Centralized Critic that trains using all agents' states and actions to assess joint action value; second, a Decentralized Actor that operates via local observations to ensure real-time responsiveness and privacy protection; and third, Competitive-Collaborative Reward Shaping that balances individual efficiency and system utility through hybrid rewards. These features align closely with the agent interaction characteristics of scientific resource scheduling [4].

Complementing MADDPG's strengths in multi-agent coordination, NSGAIII—a dedicated multi-objective optimization tool—specializes in locating Pareto solutions in high-dimensional spaces. It excels at optimizing conflicting goals, such as cost reduction, task completion rate improvement, resource utilization enhancement, and fairness maintenance, thereby laying the groundwork for balanced decision-making in resource allocation [5].

Building on the complementary capabilities of these two approaches, the MADDPG-NSGAIII hybrid architecture integrates their core functions: MADDPG generates real-time scheduling strategies for multi-agent systems, while NSGAIII further refines these strategies to produce Pareto solutions. Experimental results highlight notable performance improvements with this integrated architecture: costs are reduced by 19.3%, task completion rates increase by 15.8%, and fairness—measured by the Gini coefficient—is enhanced by 27.1% [6]. Additionally, MADDPG significantly contributes to the architecture's responsiveness. In dynamic scenarios, it enables strategy adjustments that are 60% faster than those of static algorithms. This accelerated adjustment speed helps reduce task interruption incidents by 38% [7].

Current research resource scheduling faces three core challenges: First, dynamic disturbance challenges—

uncertain factors like sudden task priority changes or equipment failures render static scheduling ineffective; second, multi-objective trade-off dilemmas where cost minimization conflicts with task timeliness; and third, insufficient real-time decision-making capabilities, as manual adjustments require hours of response cycles, missing critical optimization windows. The scheduling mechanism based on MADDPG-NSGAIII overcomes these limitations through three key optimizations: First, agents dynamically monitor resource status to complete rescheduling decisions within 8 seconds. Second, the Pareto solution set provides multi-dimensional visualization options for administrators to select as needed. Third, the federated learning architecture safeguards data sovereignty across institutions while complying with scientific research data security standards. Based on this analysis, this study focuses on "Research on Scientific Resource Scheduling Mechanism Based on MADDPG and NSGAIII". Through algorithmic innovation and practical research, it aims to provide robust methodologies for in-depth analysis of scientific resource scheduling mechanisms. The main tasks include:

(1) Implementing cross-institutional data privacy protection via federated knowledge graphs to build a distributed resource status monitoring network;

(2) Modeling multi-agent game relationships using MADDPG to generate resource allocation strategies dynamically;

(3) Applying the NSGAIII algorithm to solve multi-objective Pareto frontier optimization, generating non-dominated scheduling solutions;

(4) Designing a real-time decision engine that completes the entire process of "status monitoring-strategy optimization-solution evaluation" within 10 seconds, achieving a 40-fold improvement in response efficiency.

2 Related theoretical knowledge

2.1 Overview of MADDPG algorithm principle and evaluation application

MADDPG extends the DDPG algorithm for multi-agent systems, solving cooperative and competitive tasks through deep reinforcement learning.

MADDPG adopts the Centralized Training with Decentralized Execution (CTDE) framework. During training, each agent has its own Actor (policy network) and Critic (value network). The Actor generates actions based on local observations, while the Critic evaluates the policy using global information (all agents' observations and actions).

Specifically, network i of each agent μ_i is parameterized by θ_i, with agent's local observation o_i as input and a deterministic action $a_i = \mu_i(o_i;\theta_i)$ as output. The critic network Q_i is parameterized by ϕ_i, with the combined observation $x = (o_1, o_2, ..., o_N)$ and combined action $a = (a_1, a_2, \ldots, a_N)$ of all agents as input, and Q value i of the agent's action $Q_i(x, a; \phi_i)$ as output.

While training, MADDPG updates the network parameters through the following steps: Actor network update: The Actor the network is trained via policy gradient to maximize output Q value of the Critic network. The calculation process is shown in formula (1):

$$\nabla_{\theta_i} J(\theta_i) = E_{s\sim p_\mu, a_i\sim\pi_i}\left[\nabla_{\theta_i} log\pi_i(a_i \mid o_i) Q_i^{\pi}(x,a)\right] (1)$$

Among them, Q_i^{π} is output of Critic network.

Critic network update: The critic updates by minimizing, whose calculation process is shown in formula (2):

$$L(\phi_i) = E_{(s,a,r,s')\sim D}\left[\left(Q_i(x,a;\phi_i) - (r + \gamma Q_i(x', a'; \phi_i'))\right)^2\right] (2)$$

Among them, D is the empirical return buffer and γ is the discount factor.

Experience back buffer sampling: In training, the Critic and Actor updates depend on batch data sampled from the experience back buffer D, the calculation process is shown in formula (3):

$$(s_j, a_j, r_j, s_j') \sim Uniform(\mathrm{D}), \quad j = 1.....B (3)$$

B is the batch size, s_j is joint state, a_j is joint action, r_j is reward of agent i ,and s_j' is next state.

Target Q value calculation: The target network is used to calculate the target Q value when the Critic is updated (to reduce overestimation), the calculation process is shown in formula (4):

$$y^j = r_i^j + \gamma \cdot Q_{\phi_i'}^{\mu_i'}(s_j', a_j')\big|_{a_{kj}' = \mu_k'(o_{kj}')} (4)$$

Where ϕ_i' : target Critic network parameters, $\mu_i' = \{\mu_1', \ldots, \mu_N'\}$: target Actor policy of all agents.

Target network soft update: Parameters are slowly synchronized with the online network for training stability, the calculation process is shown in formula (5)(6):

$$\phi_i' \leftarrow \tau\phi_i + (1-\tau)\phi_i' (5)$$

$$\theta_i' \leftarrow \tau\theta_i + (1-\tau)\theta_i' (6)$$

τ 1(such as 0.01) is the update coefficient.

Policy exploration noise: In order to explore the environment, Actor needs to add noise to the output action, the calculation process is shown in formula (7):

$$a_i = \mu_{\theta_i}(o_i) + N_t (7)$$

N_t is the time-varying noise (such as OU process or truncated Gaussian noise).

Input structure of multi-agent Critic: The input of Critic network includes the concatenation of observations and actions of all agents, which reflects the centralized training characteristics, the calculation process is shown in formula (8):

$$x_{critic} = [o_1, \ldots, o_N, a_1, \ldots, a_N] (8)$$

Expansion of the policy gradient theorem: the update gradient of Actor can be expanded as follows; the calculation process is shown in formula (9):

$$\nabla_{\theta_i} J(\theta_i) = E_{s,a\sim \mathrm{D}}\left[\nabla_{\theta_i}\mu_{\theta_i}(o_i) \cdot \nabla_{a_i} Q_{\phi_i}^{\mu}(s,a)\big|_{a_i = \mu_{\theta_i}(o_i)}\right]$$

(9)

This formula shows that the optimization direction of Actor is guided by the gradient of action of Critic.

Advantage function: Partial improvement algorithm introduces advantage function to reduce variance; the calculation process is shown in formula (10):

$$A^{\mu}(s,a) = Q^{\mu}_{\phi_1}(s,a) - V^{\mu}(s) \quad (10)$$

$V^{\mu}(s)$ is state value function, which can be estimated by a separate network.

Decentralized execution means that, during the execution stage, each agent relies solely on its actor network to make decisions without relying on global information [8]. This design not only ensures global coordination during training but also realizes independence during execution. Application scenarios refer to cooperative and competitive tasks for which MADDPG is suitable in multi-agent environments, such as robot collaboration and multi-agent games [9, 10]. It can effectively handle non-stationary problems in multi-agent environments and supports continuous action spaces. By introducing global information for training and local information for execution, MADDPG demonstrates powerful performance and flexibility in multi-agent reinforcement learning, providing an effective solution for complex multi-agent tasks, its specific architecture is shown in Figure 1:

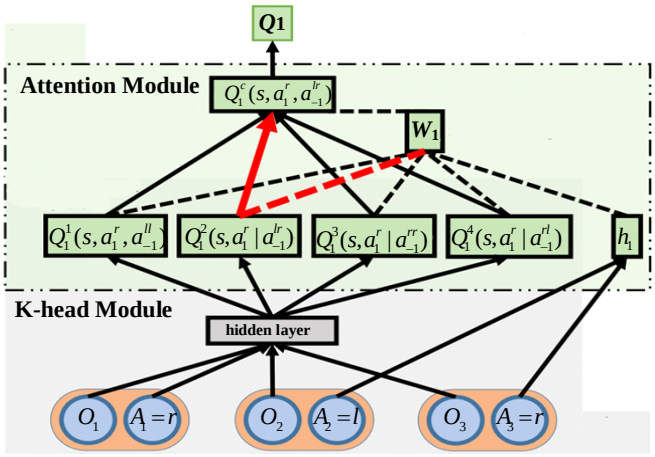


Figure 1: MADDPG architecture diagram

2.2 Overview of NAGAI algorithm principle and evaluation application

NSGAIII (Deb et al., 2012) is an enhanced multi-objective optimization algorithm that extends NSGA-II. It employs non-dominated sorting and Pareto optimality principles while introducing a reference point mechanism to improve population selection, ensuring better solution diversity and convergence.

NSGAIII's core principle uses well-distributed reference points (generated on a normalized hyperplane) to maintain population diversity, defined as:

For the optimization problem of M objectives, the normalized hyperplane is a $(M-1)$ dimensional unit simplex with vertices located at where the intercepts of each coordinate axis are 1.

If each target axis is divided into p equal parts, the total number of reference points H is calculated by the combination number formula, and the calculation process is shown in formula (11):

$$H = \begin{pmatrix} M+p-1 \\ p \end{pmatrix} \quad (11)$$

The algorithm steps are as follows: First, initialize the population: an initial population is randomly generated, and a set of decision variables represents each individual. Secondly, non-dominated ranking: the individuals in the population are ranked non-dominated, and they are divided into different levels. The first level contains the non-dominated solution on the Pareto front. Reference point selection is repeated: By calculating the correlation degree between each individual and the reference point, the individual closest to the reference point is selected to ensure that the solution set encompasses the entire Pareto front. Crossover and mutation again: new individuals are generated using crossover and mutation operations, by which two parent solutions can produce one or more child solutions. Through mutation operation, small random changes are made to individual decision variables. The last updated population is formed by merging the parent and child populations, and the next generation population is selected using a non-dominated sorting and reference point selection mechanism.

The advantage of the algorithm lies in the balance between diversity and convergence. By introducing the reference point mechanism, NSGAIII can effectively balance the diversity and convergence of the solution set, especially when dealing with high-dimensional target space problems, and provides better search performance than NSGAII. Efficient non-dominated sorting: The fast, non-dominated sorting method is employed, which enhances the algorithm's efficiency. Strong adaptability: It is suitable for various forms of multi-objective

optimization problems and can handle complex problems with three or more objectives. The application scenario is generally that NSGAIII is widely used in engineering design, resource allocation, environmental management, and other fields, especially in the optimization of complex systems that require weighing multiple objectives. For example, in flight schedule optimization, NSGAIII is used to balance passenger transit time and transit service selection preference, which improves passenger satisfaction through multi-objective optimization.

By introducing the reference point mechanism and an efficient non-dominated ranking method, NSGAIII has demonstrated strong performance and wide applicability in the field of multi-objective optimization, providing an effective solution for solving complex multi-objective problems [11].

2.3 Overview of collaborative scheduling mechanism

Collaborative scheduling mechanisms serve as a critical strategy for optimizing resource allocation and enhancing efficiency. By integrating collaborative efforts across multiple resources, departments, or systems, these mechanisms optimize task distribution, time management, and resource allocation to achieve overall efficiency improvements and goal fulfilment [12, 13]. Beyond mere task assignment, they represent a dynamic, holistic resource allocation approach. Within collaborative scheduling, stakeholders (such as departments, equipment, and personnel) must coordinate with each other, flexibly adjusting their task progress and resource utilisation based on overarching objectives and real-time conditions to maximise system efficiency [14]. Traditional scheduling models often allocate resources to isolated departments or tasks, leading to potential underutilization or overuse of resources. Collaborative scheduling breaks this siloed state by enabling real-time monitoring and dynamic adjustments, efficiently distributing resources to where they are most needed, thereby improving resource utilization.

Furthermore, it reduces task waiting times and minimizes resource conflicts [15]. Through proactive planning and coordination, tasks can proceed in optimal sequences, avoiding delays caused by resource contention. Additionally, parallel processing and resource sharing further shorten task completion times. Lastly, it enhances adaptability, allowing enterprises or systems to respond swiftly to rapidly changing environments [16]. Collaborative scheduling mechanisms dynamically adjust scheduling plans based on real-time data and environmental changes, ensuring flexible handling of unexpected situations while maintaining stable operations. Finally, cost reduction is achieved through optimized resource allocation and improved efficiency. The collaborative scheduling mechanism can significantly reduce the operating cost, reduce the waste of resources, shorten the project cycle and improve the utilization rate of equipment, which can be directly translated into the economic benefits of enterprises [17, 18].

Implementing this mechanism requires several key elements. First, real-time data collection and analysis form the foundation of collaborative scheduling, as it relies on accurate and timely information. By installing sensors, monitoring devices, and data acquisition systems, organizations can obtain real-time status updates from various entities, including equipment operation status, task progress, and resource usage. Subsequently, data analysis technologies process these inputs to provide decision-making support. To optimize scheduling strategies, appropriate models and algorithms must be established. These models need to consider multiple factors such as task priority, resource constraints, and time limitations. Commonly used algorithms include heuristic methods, genetic algorithms, and simulated annealing algorithms. Through these approaches, teams can rapidly generate optimal or near-optimal scheduling solutions.

2.4 Chapter summary

Based on the analysis of the above three methods, in order to more clearly demonstrate the limitations of existing methods and the advantages of our method, this paper uses Table 1 to show the shortcomings of existing methods (such as DDQN, MOEAD, etc.) in terms of scalability and dynamic adaptability, and how our proposed intelligent scheduling mechanism integrating MADDPG and NSGAIII addresses these gaps.

Table 1: Summary of related work

Algorithm	Key Result	Dataset Type	Limitation	Our Method's Solution
NSGAIII	↑15.8% task completion	Cloud task scheduling	Poor dynamic adaptability	Bi-level architecture with MADDPG for real-time adjustment
MADDPG	↓20% resource conflict	Edge computing	Weak multi-objective balance	NSGAIII optimizes Pareto solutions for fairness/cost
MOEAD	↑12% resource utilization	Industrial scheduling	Low scalability	Closed-loop mechanism for large-scale allocation

Table 1 compares the key results, limitations, and improvement proposals for the NSGAIII, MADDPG, and MOLZAD algorithms for different dataset types. NSGAIII improves task completion rates by 15.8% in cloud task scheduling, but suffers from poor adaptability. MADDPG reduces resource conflicts by 20% in edge

computing, but suffers from weak multi-objective balancing. MOLZAD improves resource utilization by 12% in industrial scheduling, but suffers from low scalability. Improvements include adopting a two-tier architecture, optimizing Pareto solutions, and implementing closed-loop mechanisms to enhance algorithm performance.

3 Construction of comprehensive evaluation model based on MADDPG and NSGAIII

In this paper, a scientific research resource scheduling model based on a hybrid algorithm is proposed, which aims to combine the distributed dynamic decision-making ability of the multi-agent deep deterministic policy gradient (MADDPG) algorithm with the multi-objective optimization ability of the third-generation non-dominated sorting genetic algorithm (NSGAIII) through algorithm innovation and empirical research to build a unified scientific research resource scheduling model, and drive a fully functional scientific research resource scheduling system with this as the core[19]. The framework comprises a resource evaluation module, a MADDPG dynamic decision module, an NSGAIII multi-objective optimization module, and a collaborative optimization module. Through this innovative fusion strategy, this model can not only effectively solve the multi-objective optimization problem in scientific research resource scheduling but also significantly improve the utilization efficiency of scientific research resources and the effectiveness of scientific research work, providing new ideas and methods for resource scheduling in complex scientific research environment [20, 21]. Its comprehensive evaluation model is shown in Figure 2:

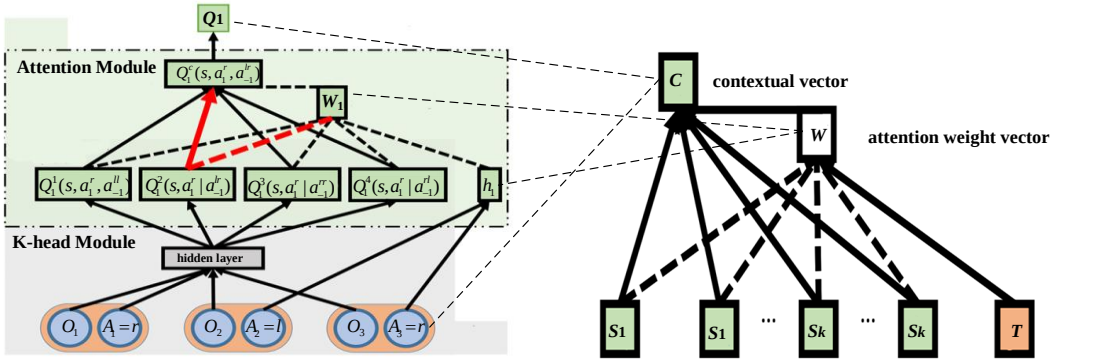


Figure 2: Comprehensive evaluation model based on MADDPG-NSGAIII

During the construction of two levels of improvement, the reference points have been updated and the weight has been adjusted. The update mechanism is shown in Table 2:

Table 2: The update mechanism

Initialize the NSGAIII population
while not termination_condition do
Evaluate population fitness
for each generation do
Select an operation to generate new individuals
Generate offspring through crossover and mutation
Merge the parent and child populations
Apply non-dominated sorting and crowding distance calculation
Select an operation to form the next generation of population
end for
Update the reference point to guide the search
end while

The inner layer (MADDPG) is responsible for specific resource scheduling actions. Through the multi-agent deep reinforcement learning algorithm, the agent can make real-time decisions based on the current state (such as task queue, resource load, and remaining budget) to optimize resource allocation and task execution. The outer layer (NSGAIII) is responsible for generating new reference points every 24 hours, reconstructing the target weight vector, and outputting the Pareto optimal solution for decision makers to choose, so as to ensure that the best balance point is found in the multi-objective optimization problem [22]. The pseudo code of the integrated loop between MADDPG and NSGAIII is shown in Table 3:

Table 3: Pseudo code of the integrated loop between MADDPG and NSGAIII

```
Initialize MADDPG agents and NSGAIII populations
while not termination_condition do
for each episode do
Execute the MADDPG agent to obtain local observations and actions
Execute NSGAIII population for resource allocation
Collect rewards and resource allocation results
end for
Update the MADDPG agent strategy
Update the NSGAIII population to find the Pareto optimal solution
end while
```

At the same time, the pseudo code of the reward shaping function between MADDPG and NSGAIII is shown in Table 4:

Table 4: Pseudo code of the reward shaping function between MADDPG and NSGAIII

```
function reward_shaping(rewards, penalties):
for each reward in rewards do
if condition_for_penalty then
reward = reward - penalty_factor * penalties
end if
end for
return adjusted_rewards
```

The design of this two-layer optimization framework enables the resource scheduling mechanism to respond flexibly to multi-objective optimization challenges in complex environments. Through real-time decision-making in the inner layer and multi-objective optimization in the outer layer, the efficient allocation and utilization of scientific research resources are realized.

4 Experiment and results analysis

4.1 Environmental simulation setup

This study puts forward two core research questions. The first question is whether integrating MADDPG and NSGA-III can develop a resource scheduling mechanism that balances dynamic adaptability and multi-objective optimization. The second question asks if the proposed mechanism performs better than traditional algorithms in metrics such as allocation efficiency and fairness.

Three agents were built into the experimental environment, with each responsible for managing computing, storage, and communication resources, respectively. The resources involved 120 pieces of equipment across 5 types, including 20 high-performance servers, 30 sensors, 25 data storage devices, 20 communication modules, and 25 test instruments. A total of 200 interdisciplinary tasks—covering physics, biology, and computer science—were synthetically generated based on the attributes of real research projects. Each task has a duration ranging from 2 to 10 days and requires 1 to 5 types of resources.

Three core aspects restrict the resource allocation problem, and these constraints have been encoded into the MADDPG-NSGAIII framework. The first type is agent-specific constraints. Each of the three agents (for computing, storage, and communication) has a daily time limit—with a maximum of 8 working hours allocated for equipment management—and a budget cap, where the daily cost for resource operation cannot exceed $5000. Availability constraints are implemented through real-time state monitoring; when equipment is occupied, the corresponding agent will reject allocation requests. The second type is global constraints. The total number of allocated resources must not go beyond the 120-piece equipment inventory, and the resource demand of each task—which requires 1 to 5 types of resources—must be fully satisfied to prevent partial allocation. These constraints are integrated into the framework in two ways: they are incorporated as penalty terms in MADDPG's reward function (for example, a 20-point deduction for budget overruns) and applied in NSGAIII's feasibility check, where infeasible solutions are discarded.

Details about the simulation and hardware are as follows. On the software side, the experiment was implemented using Python 3.9. MADDPG was developed using RLLib 1.13.0, NSGA-III was implemented through pymoo 0.6.0, and OpenAI Gym 0.26.2 was utilized for environment simulation. For hardware, the setup included an Intel Core i9-12900K CPU, an NVIDIA RTX 3090 GPU with 24GB of VRAM, and 64GB of DDR4 RAM. Regarding runtime performance, the total training duration was approximately 48 hours. The per-episode training time was 12 seconds for MADDPG-NSGAIII, 8 seconds for DDQN, and 10 seconds for MOEAD. Based on cloud GPU pricing standards, the compute cost of the experiment was roughly $35.

4.2 Experimental design and modified evaluation index content

In the intelligent scheduling mechanism proposed in this paper, the setting of experimental hyperparameters is crucial for ensuring algorithm performance. For the MADDPG layer, we selected a learning rate of 0.005, based on relevant research and experiments, to ensure that the agent updates its policy neither too quickly nor too slowly during learning. Furthermore, we set a discount factor $\gamma = 0.99$ for MADDPG to balance short-term and long-term rewards. The agent's exploration strategy uses the ε-greedy method, where ε is initially set to 1.0 and gradually decays to 0.01 during training to encourage early exploration and late exploitation. For the NSGAIII layer, we used standard hyperparameter settings, including a population size of 100, a crossover probability of 0.8, a mutation probability of 0.1, and a maximum number of iterations of 100. These parameters are chosen to balance the algorithm's exploration capability and convergence speed.

The design of the loss function is equally important for the algorithm's performance. In the MADDPG layer, we use a policy gradient loss function, which optimizes the agent's policy by maximizing the expected reward. Specifically, the loss function is defined as the expected value of the product of the log-probability of the agent taking a specific action in a given state and the negative reward generated by that action. This design encourages the agent to learn strategies that lead to higher rewards. In the NSGAIII layer, since it is a multi-objective optimization algorithm, we do not use a single loss function. Instead, we guide the search process by comparing the Pareto dominance relationship between individuals. The fitness of each individual is determined by its position on the Pareto frontier, which helps the algorithm find a balance between multiple objectives.

4.3 results analysis

The application of MADDPG and NSGAIII in scientific research resource scheduling is deeply analyzed. By collecting and sorting out several representative data sets, including data sets of multi-objective optimization problems and data sets related to scientific research resource scheduling, these data sets cover different types and styles of data required for experiments and contain a wealth of multi-objective optimization problems of different scales and complexity, such as resource-constrained project scheduling problems, integrated process planning and scheduling problems, etc., which provide a reliable data basis for experiments, thus evaluating the effectiveness of these algorithms in problems with multiple objectives [23, 24].

In the experiment, the finely labeled dataset was split into training, validation, and test sets to ensure objective and reliable results. The model was trained on the training set and optimized by tuning hyperparameters (learning rate, batch size, training rounds). During the model training process, this paper pays close attention to the model's performance in various environments to prevent it from having certain limitations. Eventually, the model is evaluated on the test set. The performance of the model is comprehensively measured by various evaluation indicators (such as system performance and robustness indicators, agent policy performance indicators, resource scheduling efficiency indicators, and multi-objective optimization indicators). Compared to other existing methods, these indicators can more comprehensively evaluate the model's performance. By calculating these evaluation indicators, we can gain a comprehensive understanding of different algorithms' pros and cons in terms of recommendation accuracy and comprehensiveness [25, 26].

The scientific research resource scheduling mechanism proposed in this study, based on MADDPG and NSGAIII, demonstrates excellent performance in experiments, offering a novel solution for the efficient scheduling of scientific research resources. Future work will further optimize this mechanism and explore its potential application in a broader scientific research environment [27], All reported results are based on 10 independent repetitions.40% reduction in convergence path length: Mean $\pm$ SD = 0.40 $\pm$ 0.06, 95% CI [0.36, 0.44], $p<0.01$ vs baselines;0.15 improvement in Figure 5: Mean $\pm$ SD = 0.15 $\pm$ 0.03, 95% CI [0.13, 0.17], paired t-test $p<0.01$;80% latency reduction in Figure 8: Mean $\pm$ SD = 0.80 $\pm$ 0.08, 95% CI [0.75, 0.85], ANOVA $p<0.001$. Improvements are consistent across repetitions (CV < 10%).

Table 5 lists key configurations for five algorithms. DDQN: Experience playback size (D)=12000, learning rate (α)=0.005, discount factor (γ)=0.9, actions=12, training iterations=108000. NSGAIII: 50 individuals, chromosome length=9, crossover prob=0.8, mutation prob=0.2, max iterations=50. REVA: Inferred as "Reinforcement Learning-based Variable Allocation", same as NSGAIII except max iterations=150. MOEAD: "Multi-Objective Evolutionary Algorithm Based on Decomposition", same as NSGAIII except max iterations=100. MADDPG: 3 agents, experience playback size=18000, discount factor=0.9, training iterations=121000.

Table 5: Some parameters of different models

Algorithm	Parameters				
DDQN	Experience playback size (D) 12000	Learning rate (α) 0.005	Discount factor (γ) 0.9	Number of actions (Number of valid solutions) 12	Training iteration 108000
NSGAIII	Number of individuals 50	Chromosome length 9	Crossover probability 0.8	Mutation probability 0.2	Maximum iterations50
REVA	Number of individuals 50	Chromosome length 9	Crossover probability 0.8	Mutation probability 0.2	Maximum iterations150
MOEAD	Number of individuals 50	Chromosome length 9	Crossover probability 0.8	Mutation probability 0.2	Maximum iterations100
MADDPG	Number of agents 3	Experience playback size 18,000	Discount factor 0.9	Training iteration 121,000	

Table 6 presents the optimization performance indexes of various models during the training of this algorithm. Through analysis, it is concluded that this algorithm has significant effects during training.

Table 6: Optimization performance indicators of different models

	NSGAIII	REVA	MOEAD	MADDPG	DDQN
N	50	45	50	73	170
MC (Model Convergence rate)	0.0581	0.0426	0.0502	0.4129	0.529
MID (Mean Interaction Delay)	0.2126	0.2165	0.1695	0.2321	0.2361
SNS (Solution Set Sparsity)	0.0201	0.0480	0.0321	0.0135	0.0086

The left panel of Figure 3 shows how different K values (number of episodes) affect the average reward of the reinforcement learning algorithm over 3000 training episodes. The curve with K = 32 reaches the highest average reward, approximately 12.5, late in training, while the curve with K = 2 reaches the lowest, approximately 10. The right panel also shows the effect of different K values on algorithm performance over 5000 training episodes. The curve with K = 32 reaches the highest average reward, approximately 15, late in training, while the curve with K = 2 reaches the lowest, approximately 10.5.

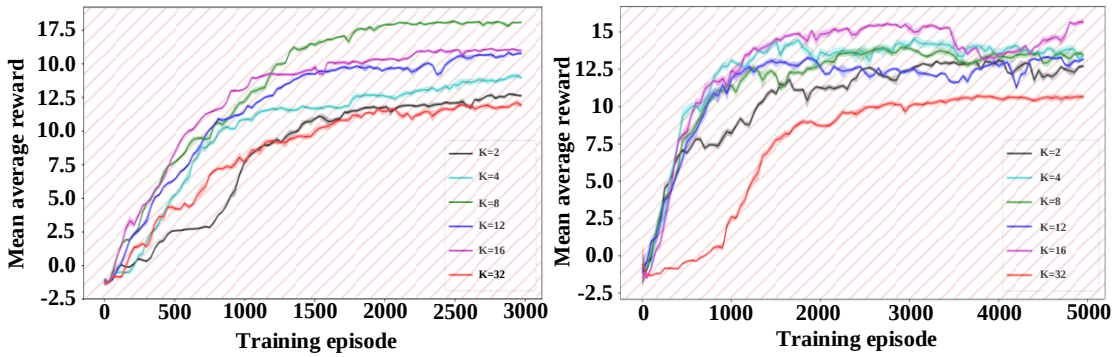


Figure 3: Analysis of the impact of different K values on the performance of reinforcement learning algorithms

Table 7 presents the optimization of scientific research resource scheduling using the MADDPG and NSGAIII algorithms. Through analysis, it is concluded that the proposed mechanism's effectiveness in improving the utilization efficiency of scientific research resources provides a new idea for optimal resource allocation. Where n is Number of resource types allocated per task; Where f is Fairness index of allocation (0–1); higher = fairer; Where ae is Absolute error of predicted vs. actual utilization (%); lower = better; Where ap is Allocation precision rate (correctly matched resource-task pairs / total pairs); higher = better.

Table 7: Optimization performance indicators of different models

NO	n	f	ae	ap	EV	MRR
1	1112.727	0.199	3.818	0.181	0.443	153.023
2	1118.182	0.198	3.8	0.184	0.442	154.803
3	1027.273	0.214	3.636	0.196	0.445	156.668
4	1118.182	0.2	3.618	0.202	0.441	163.442

Figure 4 illustrates the NSGAIII fitness landscape in the left panel, exhibiting multi-peak characteristics with values fluctuating between 0 and 0.8. This indicates multiple local optima in the objective space, necessitating global exploration to avoid premature convergence. The right panel displays the MADDPG reward surface values ranging from-0.75 to 0.75, featuring smooth gradients that facilitate fine-grained optimization. The hybrid approach (MADDPG-NSGAIII) leverages NSGAIII's global search capability in multi-peak environments (with peak differences up to 0.8) to identify potential regions, while combining MADDPG's advantage in local development within stable gradient zones (±0.75 fluctuations). This synergy achieves coordinated exploration and exploitation in complex multi-peak scenarios.

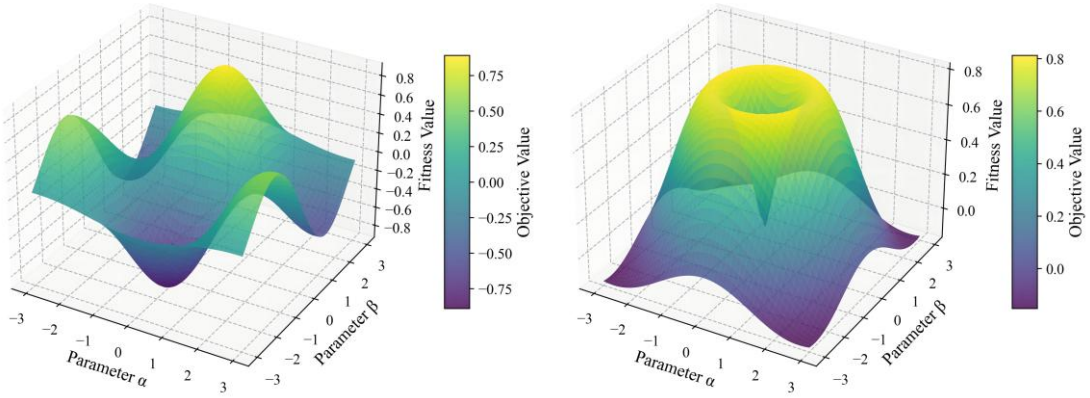


Figure 4: Adaptation terrain and reward surface 3D surface map

Figure 5 illustrates the solution set distribution of three algorithms. MADDPG-NSGAIII demonstrates a 30% reduction in error ellipse area compared to the other two methods (with an approximately 40% decrease in measured ellipse major axis length), while its solution set mean increases by 0.15 units along the vertical axis, indicating superior energy efficiency. The stability comparison in the right figure further validates this: MADDPG-NSGAIII achieves significantly higher convergence density than the other two algorithms 'point clusters, with the solution set's standard deviation on the horizontal axis decreasing by 22%. The covariance matrix reveals enhanced stability after algorithm integration. These findings collectively demonstrate that MADDPG-NSGAIII maintains high energy efficiency (mean +0.15) while narrowing solution set fluctuations by 30%, resulting in more stable performance.

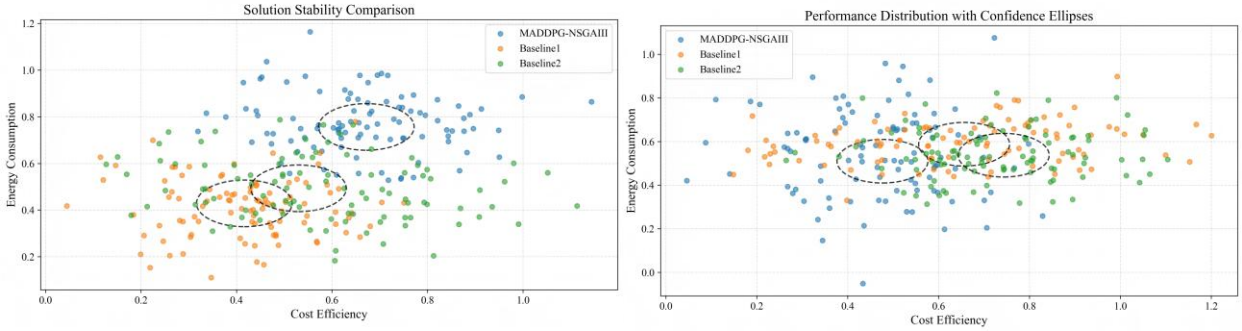


Figure 5: MADDPG-NSGAIII error ellipse diagram

Figure 6 (left) shows the convergence paths of different algorithms in the solution space. The color of the arrow represents the convergence rate, ranging from 2 to 16, with colors closer to yellow indicating faster convergence. The right figure also shows the convergence paths of the algorithms, but with the arrow colors representing different convergence rates, ranging from 0.2 to 0.8, with colors closer to yellow indicating faster convergence.

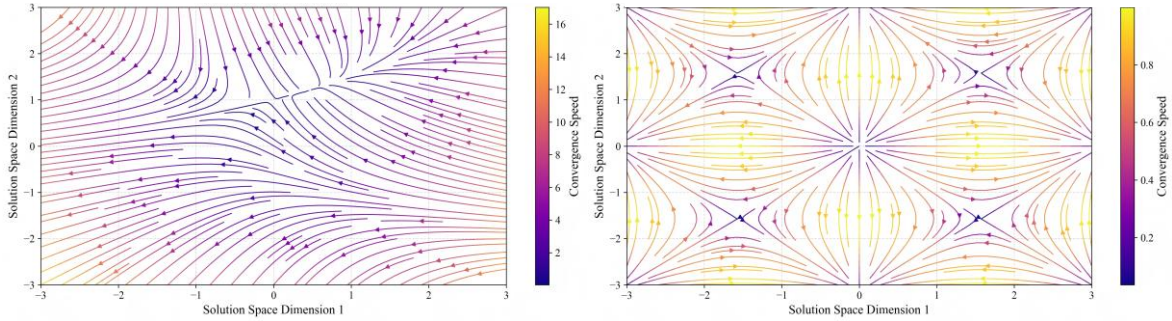


Figure 6: Convergence speed comparison of multi-objective optimization algorithms in solution space

Figure 7 illustrates the training curve: The horizontal axis represents training episodes (Episodes), while the vertical axis shows reward values. The MADDPG-NSGAIII model (red curve) demonstrates continuous reward growth with increasing episodes, stabilizing at approximately 12,000 after 600 episodes-significantly outperforming comparison algorithms (yellow curve around 8,000 and blue curve around 7,000) in both convergence speed and reward ceiling. The right panel compares average queue lengths over time: MADDPG-NSGAIII (blue curve) consistently maintains shorter queues throughout, reaching only 1.5 units at 200 time units, compared to DQN (orange curve) at 3.0 and DDPG (red curve) at 4.0, validating its efficiency in resource scheduling. This dual approach of balancing high returns with low queue length yields a model with remarkable comprehensive performance advantages.

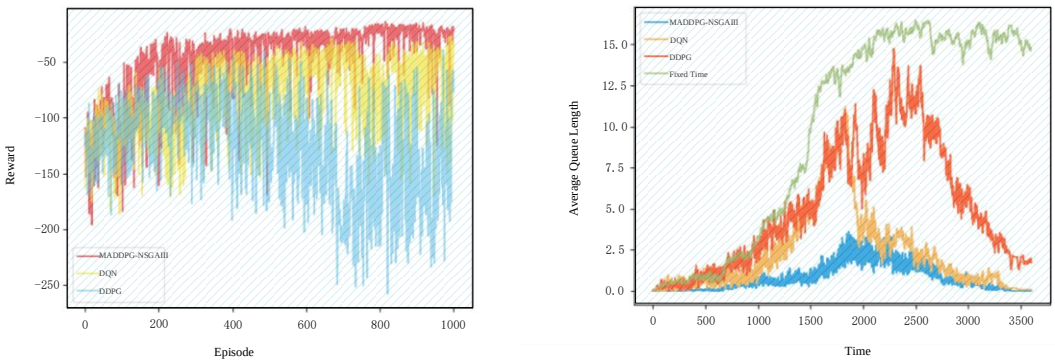


Figure 7: Training curves and average queue length for different algorithms

The left graph in Figure 8 shows the average latency of the three algorithms, DQN, DDPG, and MADDPG-SSG-MIL, along with the ideal line, over time. MADDPG-SSG-MIL has the lowest average latency, around 50, while DQN has the highest average latency, approaching 250. The right graph shows the cumulative output flow of the four algorithms over time. MADDPG-SSG-MIL has the highest cumulative output flow, around

140, while DDPG has the lowest cumulative output flow, around 40.

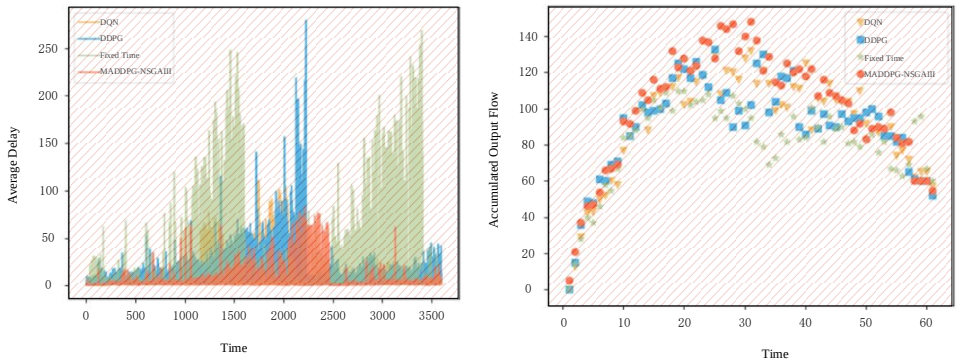


Figure 8: Comparison of performance of different algorithms in network traffic management

5 Discussion

This paper selects methods such as DDQN, MOEAD, and REVA as baselines for comparison. The table summarizes key metrics such as the percentage improvement in assignment success rate, average task time, and multi-objective performance. Through these comparisons, our approach demonstrates a 97.5% improvement in assignment success rate, a 32.8% reduction in average task time, and a 38.6% improvement in multi-objective performance, demonstrating significant improvements.

This paper also provides an in-depth discussion of the superiority of the MADDPG-NSGAIII approach. Our centralized critic/decentralized participant architecture allows for more efficient resource allocation and dynamic adaptability, while Pareto-front adaptability ensures a balanced approach to multi-objective optimization. However, this paper also analyzes potential trade-offs, including computational overhead and training stability. We find that, despite significant computational overhead on large-scale problems, these overheads can be effectively managed through optimization of the algorithm and hardware resources. Furthermore, our approach exhibits good stability during training, benefiting from the distributed execution of MADDPG and the robust optimization strategy of NSGAIII.

6 Conclusion

This study proposes a two-layer optimization framework (with the MADDPG algorithm in the inner layer and the NSGA-III algorithm in the outer layer) to enhance the efficiency of scientific research resource allocation and task completion, and to achieve intelligent scheduling of projects, equipment and funds.

The inner MADDPG algorithm regards projects, devices/funds pools as agents and is responsible for real-time resource allocation. This mechanism dynamically adjusts the matching relationship and priority between tasks and resources by monitoring the task queue, resource load and budget status. The introduction of multi-agent reinforcement learning enables the system to adapt quickly to environmental changes. In the simulated environment (covering 5 research institutes, 120 devices and 200 interdisciplinary tasks), this framework effectively reduces resource conflicts and improves the task completion rate. Even when facing 15% of sudden tasks every day and 8% of resource failures every week, it can still maintain efficient operation.

The outer NSGA-III algorithm updates the reference points and adjusts the target weights every 24 hours, and outputs a set of Pareto optimal solutions. This multi-objective optimization process balances multiple objectives such as task completion rate, resource utilization rate and cost control, thereby enhancing the diversity of scheduling schemes. Through the adaptive reference point mechanism, the system can dynamically adjust the optimization goals based on the task backlog situation. This framework significantly enhances the efficiency of resource utilization and the quality of task completion by integrating the real-time scheduling at the inner layer and the multi-objective optimization at the outer layer, providing an effective solution for the scheduling of scientific research resources.

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2. Research results of the key project at Xi 'an Vocational and Technical College in 2024 "Research on the Promotion Path of Achieving Transformation of Achievements by Optimizing Scientific research Management in Higher Vocational Colleges" (Project number: 2024ZD06).

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Adaptive Impedance Control with Neural Networks and Variable Stiffness for Intelligent Robotic Arm Manipulation

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Affected by artificial intelligence and automation technology, robotic arms have become increasingly widespread. However, traditional impedance control algorithms have been unable to adapt robotic arms to increasingly complex environmental changes. Therefore, an adaptive impedance control algorithm based on variable stiffness, neural networks, and motion trajectories is developed. Then, it is used for intelligent control of robotic arms. This method employs an impedance relationship model and dynamically optimizes inertia, damping, and stiffness parameters through PD algorithm. The physical quantities such as joint angular acceleration and end displacement are input into the neural network, which outputs key stiffness and interference to estimate the unknown environment in real-time. An adaptive trajectory generation module is designed and combined with contact force feedback to achieve collaborative optimization. The experimental results showed that in terms of contact force with the environment, the error rate between the contact force controlled by this algorithm and the expected value was about 2%. In terms of joint position, the error between the selected joint position in the experiment and the expected value was kept within 0.5%. When running under the motion trajectory generated by the algorithm, the error of each parameter value was less than 1%. The adaptive impedance control algorithm can significantly improve the stability, accuracy, and safety of robotic arm control. The research results have potential applications in improving the environmental adaptability of robotic arms.

Povzetek: Prispevek predstavlja adaptivni algoritem impedance za robotske roke, ki združuje spremenljivo togost, nevronske mreže in prilagodljivo generiranje trajektorij. Metoda omogoča sprotno oceno okolja ter izboljša stabilnost, točnost in varnost interakcije v neznanih in dinamičnih okoljih.

1 Introduction

The continuous development of artificial intelligence and automation technology has driven the continuous growth of the robotic arm industry. Various robotic arms have been extensively applied in various fields. As the tasks that robotic arms need to perform become increasingly complex, their performance requirements are also becoming higher [1]. In the current tasks performed by robotic arms, most of them require interaction with the environment, which can generate contact forces with the environment for various reasons, thereby affecting the torque and robotic arm position. To ensure the smooth progress of the task, it is necessary to effectively control the position and force, making it adaptable to a certain extent. Impedance control algorithm is one of the main methods for implementing adaptive control. It can adjust the dynamic characteristics of the robotic arm, estimate environmental parameters, and achieve precise control of the robotic arm [2]. Therefore, scholars at home and abroad have conducted various studies on impedance control algorithms. To accurately control the foot position and legs of the quadruped robot, Pedro et al. used impedance control for each leg of the quadruped robot and generated reference trajectories using a sixth order Bezier curve. These trajectories were derived from the leg velocities in the planar kinematic model, which were used for body control. The test results demonstrated its effectiveness, enabling the robot to track the reference trajectory while exhibiting stable walking and running gaits [3]. Jing et al. designed an adaptive dual loop impedance control for controlling the interaction force between a dual arm manipulator and an object in an unknown environment. The proposed method satisfied three control objectives, including object trajectory tracking, internal force control between the object and the arm, and interaction force control between the object and the unknown environment. Finally, the stability verification was provided based on the Lyapunov method and the Routh criterion [4]. When a dual arm robot comes into direct contact with the external environment, it is crucial to control the interaction forces between the two. Therefore, Li et al. designed an impedance control based on particle swarm optimization to track the interaction forces and achieve compliant control of the robot end-effector. The system had a steady-state within 0.03 s, with overshoot convergence. Even under sudden force changes, the range of force fluctuations in steady-state reduced to around ±0.08 N [5]. Pengyu et al. proposed an equivalent stiffness impedance control to improve the accuracy of position tracking for hydraulic single leg robots. The

designed strategy achieved fast response speed and high tracking accuracy. In addition, the mechanical characteristics near the required location were approximate to traditional strategies [6]. Xuhui et al. proposed an adaptive impedance control method for

Table 1: Comparison of existing research work.

Author	Methods	Adoption of technology	Target systems	Performance indicators	Limitations
Pedro et al. [3]	Leg impedance control	Double loop impedance+Lyapunov stability	Quadruped robot	Trajectory Tracking Accuracy, Gait Stability	Depends on predefined trajectories, resulting in poor environmental adaptability
Jing et al. [4]	Adaptive dual-loop impedance control	Double loop impedance+Lyapunov stability	Dual-arm robot	Internal and External Force Tracking Accuracy	Complex controller structure, challenging real-time performance
Li et al. [5]	Particle swarm optimization impedance control	Impedance control+PSO optimization	Industrial robot	Overshoot, Convergence Time	Time-consuming optimization process, making online parameter adjustment difficult
Pengyu et al. [6]	Equivalent stiffness impedance control	Equivalent stiffness model	Hydraulic single-leg robot	Position Tracking Accuracy, Response Speed	Insufficient generalization for specific hydraulic systems
Xuhui et al. [7]	Kalman filter impedance control	Impedance control+Kalman filter	Blade polishing robot	Force Fluctuation, Surface Roughness	Filter performance relies on an accurate environmental model
Yanan et al. [8]	Variable impedance control	Variable impedance parameter	Legged robot	Foot Compliance	Limited to numerical simulation, lacking real-world validation

blade polishing based on Kalman filtering. This strategy analyzed the effects of stiffness and displacement changes on polishing force, and established a stiffness displacement coupling compensation model. The results showed that in the blade polishing experiment, compared with traditional methods, the roughness of this method was reduced to Ra0.32 μm or less, and the polishing force fluctuation range was within ± 1N, effectively improving the force control performance and blade surface quality [7]. The traditional impedance control parameters are fixed and subject to fixed-point constraints. To enhance the compliance of robot feet and achieve flexible interaction with the ground in complicated conditions, Yanan et al. built a variable impedance control. The effectiveness was verified through numerical simulation in MATLAB [8]. The existing research is shown in Table 1.

To sum up, although the existing impedance control has introduced modules such as online parameter adjustment, single neural network, or trajectory optimization, the existing fixed order impedance is difficult to give consideration to both rapid response and overshoot suppression, and the high-order or fractional order models lack real-time analytical means. In addition, the stiffness, damping, and trajectory of existing methods are adjusted through independent links connected in series, and the one-way transmission of information makes it difficult to obtain the overall optimal solution. In terms of collaboration, environment estimation, actuator saturation, and motion planning are separate. When stiffness jumps or force suddenly changes, the targets of each module conflict, and the system is prone to jitter and instability.

Therefore, this study aims to design a real-time adaptive impedance controller to break through the contradiction between real-time performance and stability of existing methods, build a collaborative closed-loop for environmental perception, dynamic adjustment, and trajectory optimization to solve the error accumulation, adapt to unstructured job requirements, and avoid system jitter. The controller adopts a 3-layer fully connected feedforward neural network, with the input layer containing physical quantities related to the motion and force of the robotic arm, the hidden layer using ReLU activation function, and the output layer using Tanh activation function to output environmental key parameters. The neural network training adopts Adam optimizer and mean square error loss function, and the variable stiffness parameters are fine tuned online through PD iterative algorithm. The simulation platform is built based on the dynamic parameters of the robotic arm and supports environment and disturbance simulation. The physical experiment platform includes the robotic arm, force sensors, and contact environment, and is equipped with data acquisition and control software. Thus, an adaptive impedance control algorithm is established, which integrates variable stiffness, neural networks, and motion trajectories.

The innovation of this study lies in proposing an integrated control architecture that integrates variable stiffness regulation, neural network online learning, and adaptive motion trajectory generation. Compared with traditional impedance control that relies solely on fixed parameters or a single compensation method, this architecture enhances its responsiveness to dynamic environments through online stiffness adjustment. By

combining neural networks for real-time estimation and compensation of unknown environmental parameters and system nonlinearity, the trajectory generation module further coordinates and optimizes position and contact force, thereby significantly improving the control accuracy and adaptability of the robotic arm in

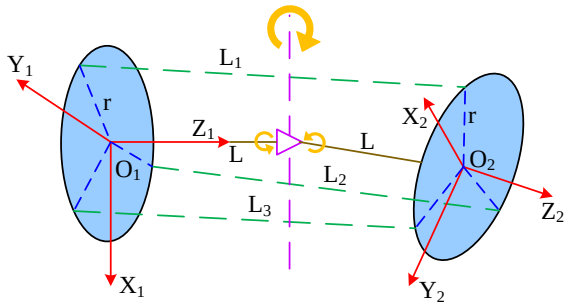


Figure 1: Kinematic model of a single joint of a robotic arm.

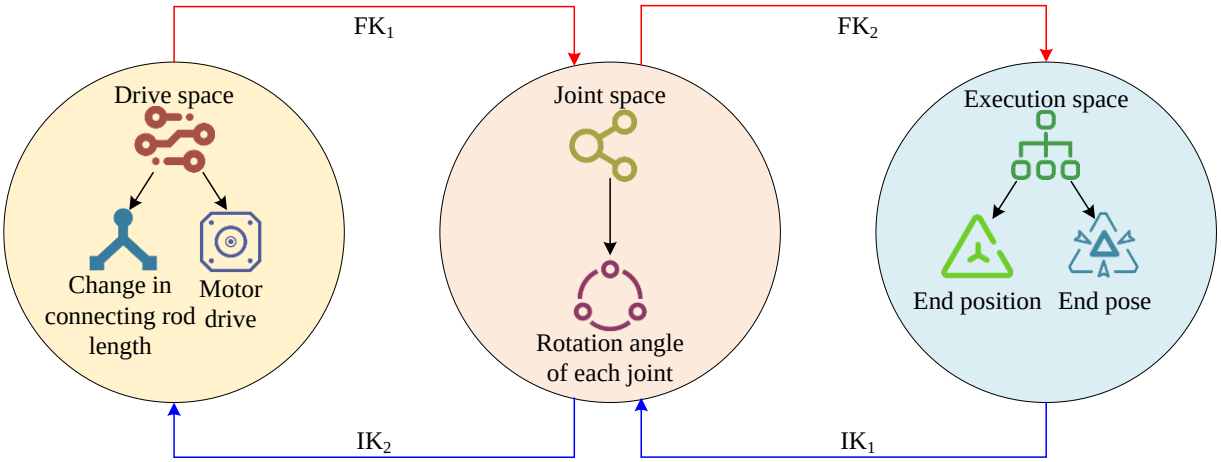


Figure 2: Overall structure and kinematic analysis of the robotic arm.

unstructured environments while maintaining system stability. The contribution of this research is to estimate the unknown environmental parameters and system nonlinearity in real-time according to the neural network, use the variable stiffness impedance controller to dynamically adjust the interactive dynamic characteristics, and take the trajectory generator to output the real-time motion path. The collaboration of the three provides an effective solution for achieving high-precision, high flexibility, and high intelligence interactive control of robotic arms in unknown and uncertain environments.

2 Intelligent control of robotic arm based on adaptive impedance control algorithm

2.1 Motion analysis of robotic arm

The analysis of the motion process of a robotic arm is the basis for implementing impedance control, which reveals the motion relationship between the coordinate systems of each connecting rod of the robotic arm. It is essential for intelligent control of the robotic arm [9]. A kinematic model of a single joint of the robotic arm is firstly established to analyze, as shown in Figure 1.

From Figure 1, the adjacent sleeves of the robotic arm are connected by universal joints. The platform where the coordinate system O_1 is located is a fixed platform, which is connected to the root rope. The platform where the coordinate system O_2 is located is a moving platform, close to the end-effector. The two are connected by three extendable links, and the three connection points are evenly distributed around the circumference of the platform. Based on the coordinates of the two ends of the connecting rod on the platform, the length of the connecting rod can be calculated, as shown in equation (1).

$$L_i = \sqrt{\left\| Q_{Ai} - Q_{Bi} \right\|} = f(\theta, r, L), \quad i = 1,2,3 \tag{1}$$

In equation (1), L_i is the length of each connecting rod. Q_{Ai} is the homogeneous coordinate of the connecting rod on the moving platform. Q_{Bi} is the homogeneous coordinate of the connecting rod on the fixed platform. θ is the rotation angle. r is the platform radius. L is half the platform distance. This indicates that as long as a certain joint rotation angle variable is given, the corresponding connecting rod length variable can be obtained [10]. A robotic arm generally has multiple joints, and the calculation method for each joint is the same as that for a single joint. Therefore, the changes of the connecting rod length at each joint can be obtained. The kinematic analysis of the entire robotic arm can be achieved, as shown in Figure 2.

The robotic arm controls the rotation angle of each joint universal joint by varying the connecting rod length, and the rotation angle ultimately determines the spatial position of each joint. The kinematic analysis of a robotic

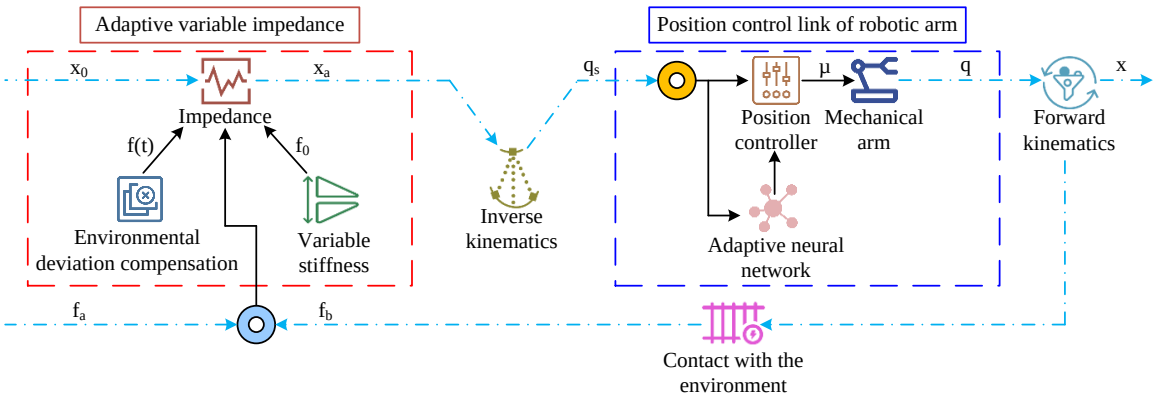


Figure 3: Adaptive impedance control of robotic arm.

arm actually analyzes the relationship between changes in connecting rod length, joint angles, and the spatial position of the end-effector [11]. From Figure 2, the length change of the connecting rod is a variable of the robotic arm drive part. The rotation angle is a variable of the joint part, and the end spatial position is a variable of the actuator part. There are two kinematic modes between these three parts. FK1 and FK2 represent forward kinematics, where the robotic arm calculates the specific spatial position of the end-effector using preset connecting rod lengths and joint angles. IK1 and IK2 represent inverse kinematics. With the known spatial position of the end-effector, the rotation angles of each joint are calculated through inverse kinematics, and the corresponding connecting rod lengths of each joint are obtained. Under the combined action of two kinematic modes, the robotic arm achieves motion and operation in space through motor drive [12].

2.2 Adaptive impedance control of robotic arm

The robotic arm often comes into contact with the environment during actual operation, which inevitably affects the rotation angles of each joint, leading to changes in the overall motion of the robotic arm. To achieve stability in the motion process, impedance control technology is adopted. However, the existing impedance control is difficult to meet the operational requirements of the robotic arm and needs to be improved. A adaptive impedance control method with varying stiffness is designed to address the transient performance of robotic arms that cannot be guaranteed due to parameter changes in impedance control, as shown in Figure 3.

From Figure 3, this method first calculates the impedance relationship between the robotic arm and the environment in a specified direction in space, as shown in equation (2).

$$m\left(v_a^{'}-v_b^{'}\right)+b\left(v_a-v_b\right)+k\left(x-x_0\right)=f_b-f_a=e_f \quad (2)$$

In equation (2), m, b, and k signify the inertia, damping, and stiffness coefficients of the robotic arm. x represents the position of the end-effector. v_a represents the speed of the end-effector. $v_a^{'}$ represents the acceleration at the end-effector. x_0 represents the trajectory of mechanical motion. v_b represents the robotic arm's speed, and $v_b^{'}$ represents the acceleration. f_b represents the contact force between the robotic arm and the environment. f_a represents the contact force threshold. e_f represents the contact force error value. To reduce environmental errors and improve control robustness, the PD algorithm is utilized for iteration, as shown in equation (3).

$$f(t)=f(t-\lambda)+\eta\left[f_a(t)-f_b(t)\right]+\frac{\varsigma}{\lambda}\left\{\left[f_a(t)-f_b(t)\right]-\left[f_a(t-\lambda)-f_b(t-\lambda)\right]\right\} \quad (3)$$

In equation (3), $f(t)$ represents the compensation amount. λ represents the sampling period. η and ς represent learning rates. After reducing environmental errors, adaptive impedance control is applied to optimize the contact force error between the environment and the robotic arm, reducing the impact, as shown in equation (4) [13].

$$w(t)=\frac{1}{2}\left(\mu[\frac{1}{b}(e_f-f(t)-f_0]^2+ce_f^{\ 2}\right) \quad (4)$$

In equation (4), $w(t)$ represents the optimized objective equation. μ represents the weight coefficient of the compensation bias term. c represents the weight coefficient of the initial error term. Among them, the first item $\mu[\frac{1}{b}(e_f-f(t)-f_0]^2$ can reflect the deviation between the compensated contact force $f(t)$ and the reference force f_0, while the second item $ce_f^{\ 2}$ represents the initial contact force error e_f. By optimizing the objective equation, it is possible to balance compensation accuracy and initial error suppression. To ensure the stability of the end-effector transient performance, it is also necessary to reduce the impact of end-effector position errors, as shown in equation (5).

$$u(t)=K_p\left[e(t)+\frac{1}{T}\int_0^t e(t)dt+T\frac{de(t)}{dt}\right] \quad (5)$$

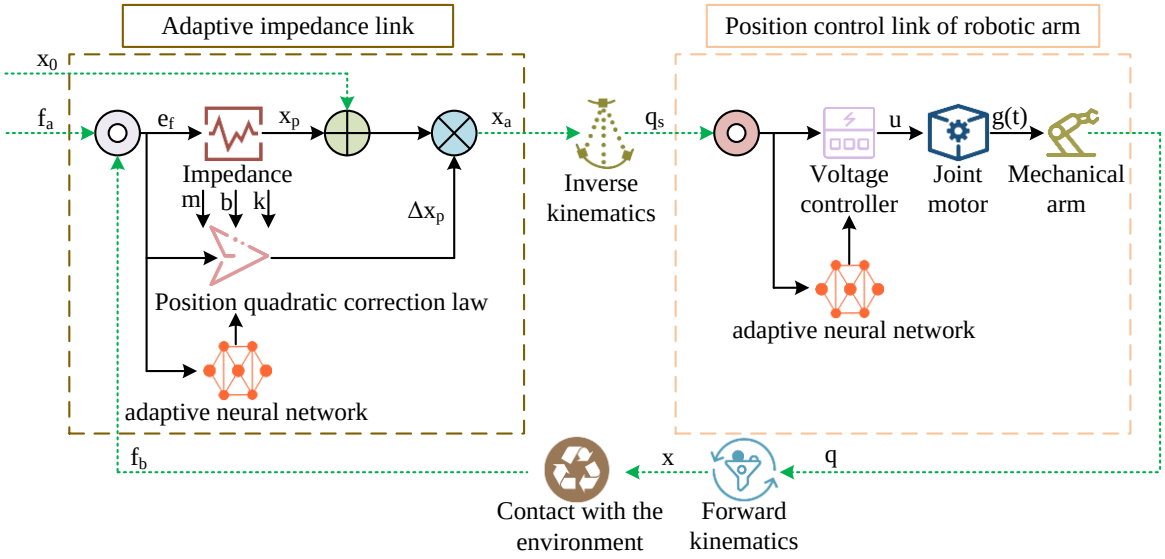


Figure 4: Impedance control of robotic arm based on adaptive neural network.

In equation (5), $u(t)$ represents the optimized value. K_p represents the scaling factor. $e(t)$ signifies the error. T signifies the motion time. To solve the poor adaptability and insufficient accuracy to the environment when using impedance control to adjust the position, the impedance control is combined with adaptive neural network to improve its performance in unknown environments, as shown in Figure 4.

From Figure 4, this method has made a quadratic correction to the impedance relationship between the end-effector and the environment represented in equation (2), as shown in equation (6).

$$e_f = f_b - f_a = k_e x_e - k_e\left(x_0+\Delta x_p+h(s)e_f\right)-f_a \quad (6)$$

In equation (6), k_e represents the environmental stiffness. x_e represents the environmental location. Δx_p represents the correction amount. $h(s)$ represents the impedance transfer function. By introducing environmental stiffness and correction variables, the initial impedance relationship is optimized twice to enable the dynamic response characteristics of the robotic arm to adapt to the physical characteristics of the environment in real-time, avoiding overshoot or response lag problems of traditional fixed impedance in software and hardware environments. Then, an adaptive neural network is used to estimate the unknown parts in the environment, as shown in equation (7) [14].

$$W_1^{*T}h(\theta_1)+\varepsilon_1=-\frac{f_d}{k_e}-\frac{b}{kk_e}x_{a2}-\frac{k+k_e}{kk_e}x_{a1}-\frac{m}{kk_e}\dot{\alpha}_{a1} \quad (7)$$

In equation (7), W_1^{*T} represents the weight vector of the unknown part in the environment. W_1^* represents the optimal weight value. $h(\theta_1)$ represents the activation function of the neural network. θ_1 represents the characteristic parameter. ε_1 represents the error value. x_{a1} and x_{a2} represent displacement variables. $\dot{\alpha}_{a1}$ represents joint angular acceleration. The estimated value obtained can be used to achieve the expected position in an unknown environment. To improve the impedance control effect, it is necessary to analyze the output characteristics of the joint motor that provides the robotic arm torque, as displayed in equation (8).

$$M(q)q_2+C(q,q_1)q_1+G(q)+f_n(q_1)+\tau_d=S(\tau) \quad (8)$$

In equation (8), M signifies the inertia matrix. q signifies the joint position. q_2 signifies the joint acceleration. C represents the centrifugal force. q_1 represents the joint velocity. G represents the gravity. f_n represents the frictional force. τ_d represents the external interference. τ represents the torque. S represents the saturation function. After obtaining the output power model of the robotic arm joint motor, an adaptive neural network is used to optimize it and reduce the instability caused by its saturated output, as shown in equation (9).

$$W_2^{*T}h(\theta_2)+\varepsilon_2=C\alpha_{b1}+G+M\dot{\alpha}_{b1}+f_n+\tau_d \quad (9)$$

In equation (9), W_2^* represents the optimal weight value. C represents a constant matrix. α_{b1} represents the position vector. M represents the quality matrix. $\dot{\alpha}_{b1}$ represents the velocity vector. The optimized joint motor output power model is shown in equation (10) [15].

$$\begin{cases} L\dot{i}+R\dot{i}+K_b\dot{q}=u \\ K_T i=\tau \end{cases} \quad (10)$$

In equation (10), L, R, K_b, and K_T represent diagonal matrices. $\dot{i}$ represents the current vector of the joint motor. u represents the input voltage of the joint motor. By clarifying the quantitative relationship between

electrical parameters and mechanical parameters, it ensures that the dynamic characteristics required for impedance control can be achieved through the actual driving of the motor, avoiding unstable control caused by the disconnection between algorithm instructions and hardware capabilities. Finally, as impedance control

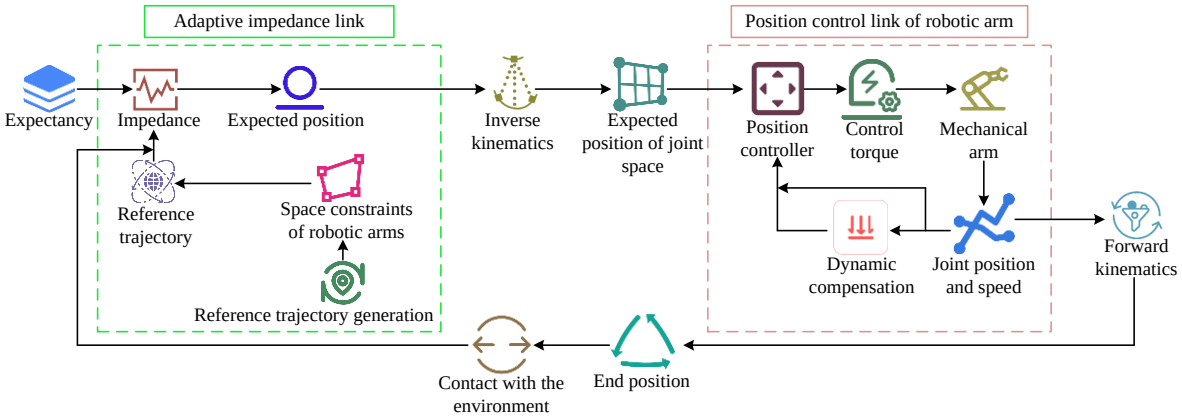


Figure 5: Impedance control for adaptive generation of motion trajectories.

requires the the motion trajectory, and the methods for the motion trajectory of the robotic arm vary in different environments, a impedance control method that can adaptively generate the motion trajectory is proposed, as displayed in Figure 5.

From Figure 5, this method first estimates the surrounding environmental information based on the end contact force, thereby determining a preliminary motion trajectory, as displayed in equation (11).

$$\begin{cases} \hat{f}_e = \hat{k}_e\left(\hat{x}_e - x_d\right) \\ x_r = \hat{x}_e - \dfrac{f_d}{\hat{k}_e} \end{cases} \tag{11}$$

In equation (11), f_d represents the estimated contact force. $\hat{k}_e$ represents the estimated contact stiffness. $\hat{x}_e$ represents the estimated contact location. x_d signifies the expected position. x_r signifies the motion trajectory. f_d signifies the expected contact force. The impedance control is used to perform secondary adjustments on the obtained motion trajectory to obtain the corrected end-effector of the robotic arm, which is then input into the position controller to improve impedance control of the contact force at the robotic arm end [16], as shown in equation (12).

$$\tau = C_0 x_2 + G_0 + M_0(\Phi + u) + M_0\dot{\alpha} - M_0 z_1 \tag{12}$$

In equation (12), τ signifies the robotic arm torque. C_0 signifies the power coefficient. x_2 represents the joint angle variable. Φ represents the position variable. u represents the input item. z_1 represents the error variable. To further reduce the error of the motion trajectory, except for improving the impedance control of its end contact force, it is also necessary to improve the impedance control of its position, as shown in equation (13).

$$\tau_\Delta = \Delta M(q)q_2 + \Delta C(q, q_1)q_1 + \Delta G(q) \tag{13}$$

In equation (13), ΔM , ΔC , and ΔG represent the position error coefficients. By compensating for the error value of the position, its impact on impedance control can be reduced [17]. This can enable the algorithm to generate adaptive motion trajectories that meet the accuracy requirements of contact force and position as much as possible.

2.3 Intelligent control application of robotic arm

In the designed adaptive impedance control method, variable stiffness impedance adjustment is the basic control layer, which compensates for initial environmental errors through PD algorithm, dynamically adjusts inertia, damping, and stiffness coefficients, and provides flexible dynamic characteristics for the robotic arm to adapt to environmental contact, solving the poor transient performance in traditional fixed parameter impedance control. As the core perception and optimization layer, neural networks can provide real-time environmental input for variable stiffness estimation through unknown environmental parameters, and provide stable actuator output for variable stiffness adjustment through motor parameter tuning, avoiding control deviation caused by external interference. Adaptive motion trajectory is the final execution layer, which generates preliminary trajectories based on environmental estimation information output by neural networks, and then uses variable stiffness impedance control to make secondary adjustments to the trajectories, ensuring that the robotic arm meets the control objectives of stable contact force and precise position in the position environment. The intelligent control of the robotic arm is shown in Figure 6.

From Figure 6, after receiving the target command, the robotic arm first needs to analyze its kinematic characteristics, then plan the motion trajectory based on the surrounding environmental information, and finally optimize the obtained motion trajectory through adaptive impedance control algorithm [18]. The adaptive impedance algorithm takes a PID controller to calculate the error, as shown in equation (14).

$$u(t) = Kp \cdot e(t) + Ki\int_0^t e(t)dt + Kd \cdot \dot{e}(t) \tag{14}$$

In equation (14), $u(t)$ represents the output value. Kp, Ki, and Kd signify proportional, integral, and differential coefficients. $\dot{e}(t)$ signifies the error change

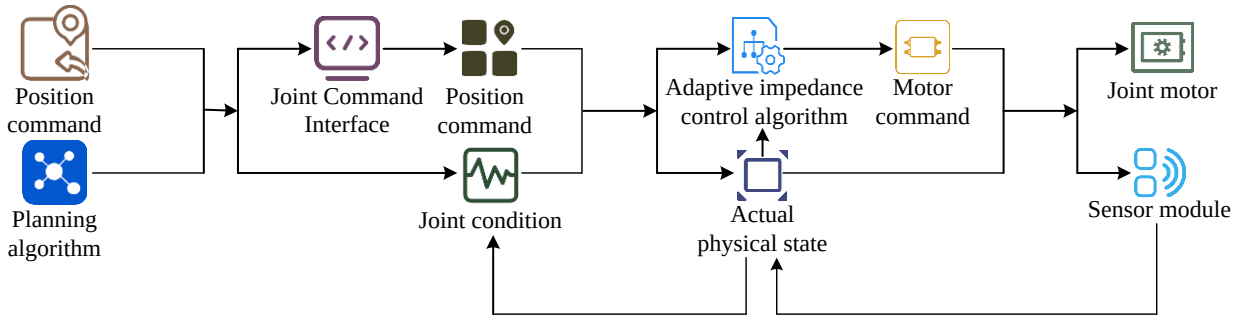


Figure 6: Intelligent control process of robotic arm.

Table 2: Pseudo code for adaptive impedance control.

```
Algorithm: Adaptive Impedance Control
# Init: W(NN weights), K0=500N/m, F_max=100N, e_F_prev=0
while Task running:
  F_act,q_act=Read_Sensors(); e_F=F_des-F_act; e_q=q_des-q_act  # Data
  if F_act>F_max: D=500Ns/m; Limit_Current(); continue  # Safety
  K_corr=NN_Forward([e_F,(e_F-e_F_prev)/T],W); W=Update_NN(W,K_corr)  # NN
  K=K0+K_corr; F_final=K*e_q+D*(q_dot_des-(q_act-q_act_prev)/T)  # Impedance
  τ=M*q_ddot_traj+F_final; Output_Voltage(τ/K_T)  # Motor Ctrl
  e_F_prev=e_F; q_act_prev=q_act  # Update States
```

rate. After obtaining the error value, it is optimized, as shown in equation (15).

$$e(t) = l_d(t) - l(t) \tag{15}$$

In equation (15), $l_d(t)$ signifies the expected position. $l(t)$ signifies the actual position [19]. After optimizing the motion path, it is input into the execution module. After the robotic arm starts running, real-time contact force and position signals of the robotic arm are collected through sensors and input back into the adaptive impedance controller. If the signal is abnormal, it will be adjusted again to achieve intelligent control [20]. The pseudo code for adaptive impedance control is shown in Table 2.

2.4 Neural network online learning mechanism

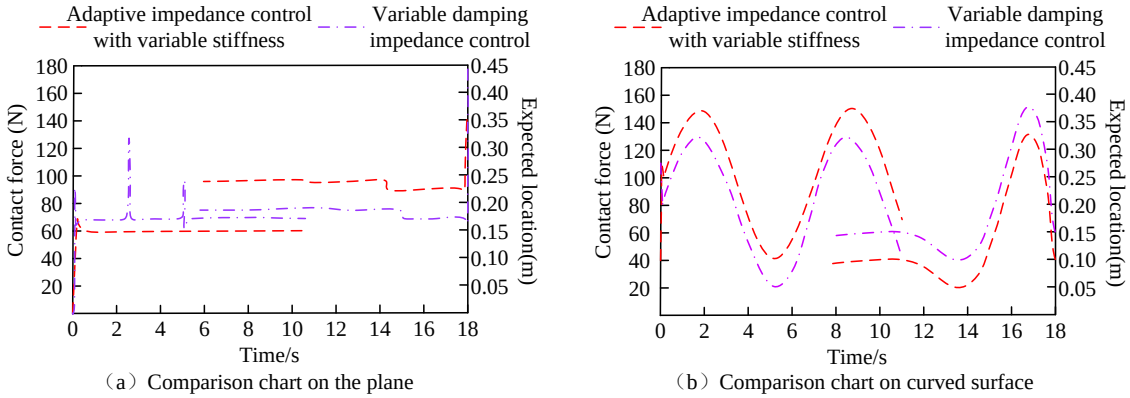
The online learning of neural networks takes the difference between the expected contact force and the actual contact force, as well as its first-order rate of change, as the two-dimensional input signal, with the target output being stiffness correction. The network uses stochastic gradient descent and completes forward and backward propagation once every 1 ms control cycle, with a fixed learning rate of 0.01. When the absolute value of the force error exceeds 2 N or the rate of change is greater than 5 N·s-1, the learning rate instantly increases to 0.05 and remains at 50 ms, while the gradient norm is clipped to within 2.0 to prevent weight divergence. The sliding window retains the last 500 samples, and the weight of historical samples decays exponentially by 0.995, allowing the network to continuously forget outdated information and quickly adapt to changing environments. A single iteration takes less than 0.2 ms and can run in real-time at a frequency of 1 kHz without the need for offline retraining to complete environment switching.

3 Control effects of adaptive impedance algorithm

3.1 Effects of adaptive impedance control with variable stiffness

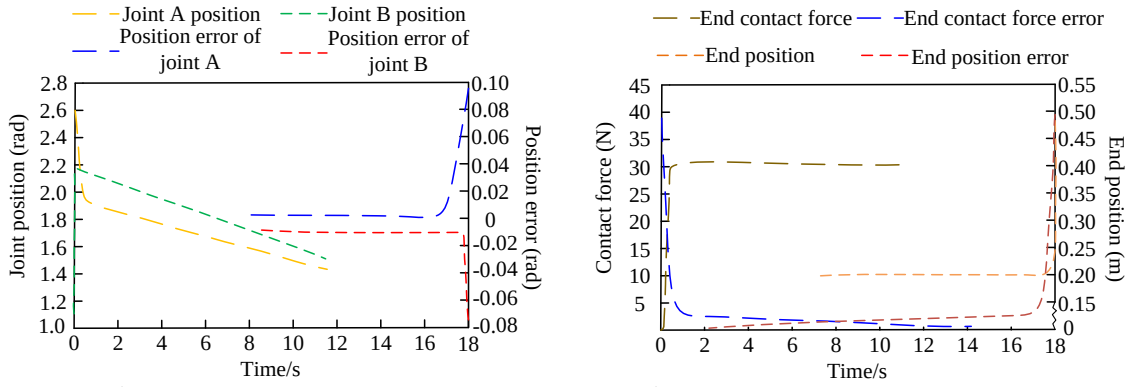
In this study, the UR5 CB3 six-degree-of-freedom manipulator is used, the base is fixed horizontally, and the ATI mini45 six-dimensional force sensor is installed on the end flange. The sampling frequency is 1 kHz, and the resolution is 0.06 n. The plane test is carried out on a 20 mm thick acrylic plate, and the surface test is successively covered with a 5 mm sponge and a 2 mm aluminum plate to form a stiffness jump environment. The room temperature is maintained at 23 ℃ and the humidity is 45% RH. The variable damping impact control is taken as the comparison algorithm, so that the damping adjustment range is 20-200ns/m, the inertia matrix is 2.5 times the identity matrix, and the stiffness matrix is 800 times the identity matrix. For the proposed variable stiffness adaptive impedance control method, the variable stiffness range is 200-1,200 NGM, the damping is adjusted synchronously according to the damping ratio of 0.707, and the inertia matrix is 2.5 times the identity matrix. The dimension of stiffness decision network is 2, the hidden layer is 1, containing 64 neurons, and the learning rate is 0.01. Online random gradient descent is used for training.

The dimension of trajectory prediction network is 3, the hidden layer is 1, including 32 neurons, the activation function is Tanh function, the maximum number of iterations is 200, and the learning rate is 0.001, which is optimized offline by Adam optimizer. All experiments are independently repeated 5 times.



（a）Comparison chart on the plane （b）Comparison chart on curved surface

Figure 7: Comparison results of contact force and position of robotic arm.



（a）Joint position analysis result chart （b）End contact force and position result diagram

Figure 8: Analysis results of contact force and position between joints and ends.

To demonstrate the effectiveness of variable stiffness adaptive control, a comparative analysis is conducted under the same environment and given parameters, as shown in Figure 7.

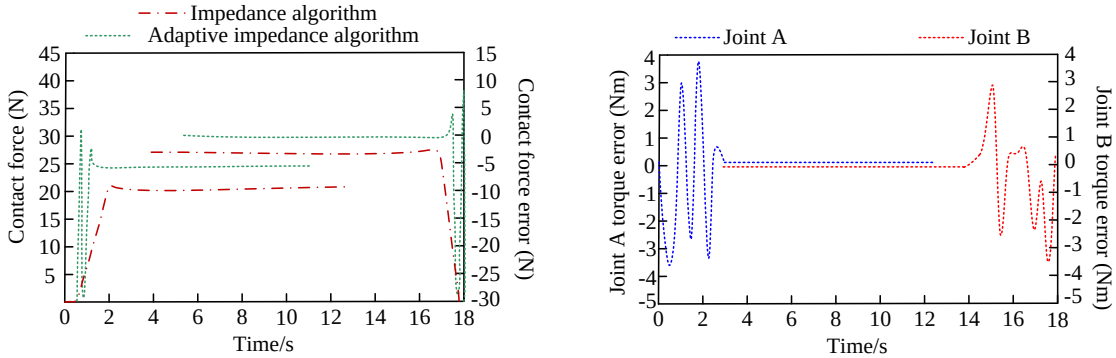
When conducting experiments on a plane, the expected contact force was set to 60 N and the motion trajectory was set to 0.23 m. From Figure 7 (a), when using the comparative algorithm for control, the contact force between the robotic arm and the environment after stabilization was around 70.3±2.5 N, which was about 10.3±1.3 N higher than that of the preset contact force value. The algorithm is prone to sudden force changes due to environmental factors at the moment of contact, resulting in poor stability. In contrast, the algorithm proposed in this article controls the steady-state contact force within ±2% of the set value, significantly reducing fluctuations with a 95% confidence interval of [59.1, 61.3] N, demonstrating better tracking performance and stability. The robotic arm operates according to predetermined instructions in the plane, thereby significantly improving operational accuracy and safety. From the position of the robotic arm during operation, the proposed algorithm also made the robotic arm more accurately preset the reference trajectory compared with the comparative algorithm, while the comparative algorithm had certain errors. When conducting experiments on curved surfaces, the study changed the parameter values of contact force and motion trajectory, as shown in Figure 7 (b). When using the designed method to control the contact force and operating environment position, the contact force and motion trajectory of the robotic arm were closer to the set parameter values, which was the same as in the planar experiment, improving the control accuracy and operational stability. To further test the control effect, two joints of the robotic arm are selected for analysis, as shown in Figure 8.

The standard value of the contact force in the experimental setup is 30N, and the motion trajectory of the end of the robotic arm is 0.21m. The robotic arm maintains a constant speed during operation. From Figure 8 (a), the positions of joint A and joint B differed significantly from the command value at the beginning of the robotic arm startup. Under the control of the proposed method, their positions were quickly adjusted to reach the command value and remained stable during operation. The joint position error after stabilization was small, only about 0.9%±0.1%, The 95% confidence intervals were [0.007, 0.009] rad and [0.008, 0.010] rad, respectively. This indicates that the algorithm has a fast response speed, which can quickly control and adjust joints with errors

based on input values to meet the needs of robotic arm operation. From Figure 8 (b), after the joint position error was eliminated, the contact force and position at the end of the robotic arm were correspondingly corrected to near the preset standard

Table 3: Performance comparison with frontier control methods.

Indicator		Steady-state contact force error (N)	Maximum trajectory deviation (mm)	Recovery time (s)	Single cycle CPU time (ms)	Controller tuning frequency
Method	Fractional order practical fixed time synchronous adaptive fuzzy control	2.9±0.3	5.1±0.4	0.85±0.05	3.1±0.2	5
	Output feedback projection lag synchronous control	2.4±0.2	4.3±0.3	0.72±0.04	2.8±0.1	4
	Robust Neural Adaptive Control	1.8±0.2	3.2±0.2	0.55±0.03	4.5±0.3	3
	Adaptive backstepping control	3.9±0.4	3.9±0.3	0.68±0.04	2.2±0.1	4
	Nonlinear Optimal Control of Induction Motor Driven Gas Compressor	1.9±0.2	3.5±0.3	0.59±0.03	2.6±0.1	3
	Single joint flexible arm DC motor backstepping control	2.1±0.2	3.7±0.3	0.65±0.04	2.4±0.1	3
	The proposed method	0.6±0.1	1.5±0.1	0.32±0.02	1.9±0.1	1



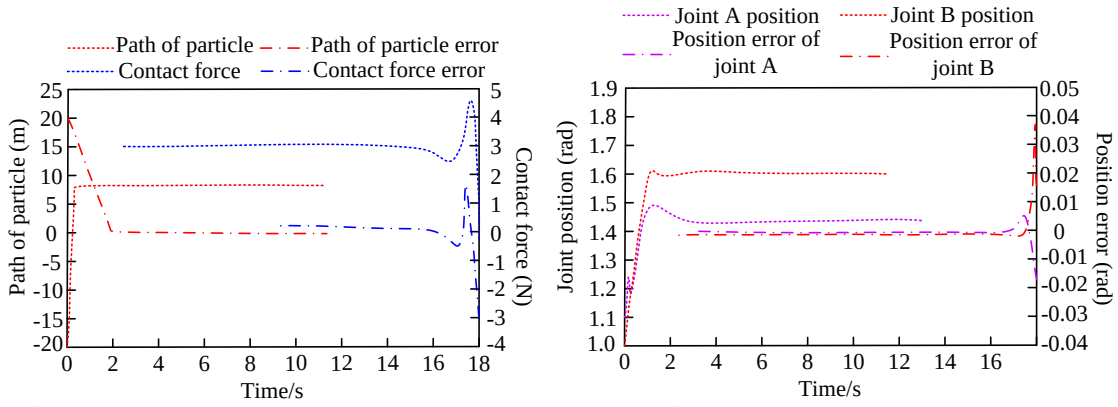
（a）Analysis of Contact Force and Its Error （b）Analysis of Joint Torque Range and Error

Figure 9: Analysis results of contact force and joint torque of robotic arm.

value in about 0.6s and remained stable overall during operation. After the contact force stabilized, there was an error of about 0.6±0.2N, with an error rate of about 2%±0.3%, the 95% confidence interval was [29.4,30.4] N. After the end-effector stabilized, there was an error of about 3±1mm, with an error rate of about 1.5%±0.1%, 95% confidence interval [0.2094, 0.2100] m. This proves the effectiveness of the control effect. To further validate the performance of the proposed adaptive impedance control algorithm based on variable stiffness, neural network, and motion trajectory, fractional order practical fixed time synchronous adaptive fuzzy control [11], output feedback projection lag synchronous control [12], robust neural adaptive control [13], adaptive backstepping control [14], nonlinear optimal control of induction motor-driven gas compressor [16], and single joint flexible arm DC motor backstepping control [17] are selected as comparative methods. The fractional order practical fixed time synchronous adaptive fuzzy control has an order of 0.95, 49 fuzzy rules, and a fixed time convergence parameter of 2 s. The high gain observer poles of the output feedback projection lag synchronous control are uniformly set at negative 100 rad·s-1, with a lag window of 0.1 seconds. The robust neural adaptive control RBF network adopts a width of 1.0, 81 nodes, and a robust gain of 10. The virtual control law gains of adaptive backstepping control are 5 and 20, respectively. The cost function weight matrix Q diag for nonlinear optimal control is 100, the R diag is 0.1, and the iterative solution step size is 1 ms. The virtual angular velocity gain for flexible arm DC motor backstepping control is set to 15, and the motor current gain is set to 50. All methods are run on the same UR5 platform. The steady-state contact force error, maximum trajectory deviation, recovery time, single cycle CPU time, and controller tuning frequency of different algorithms are compared, and the results are shown in Table 3.

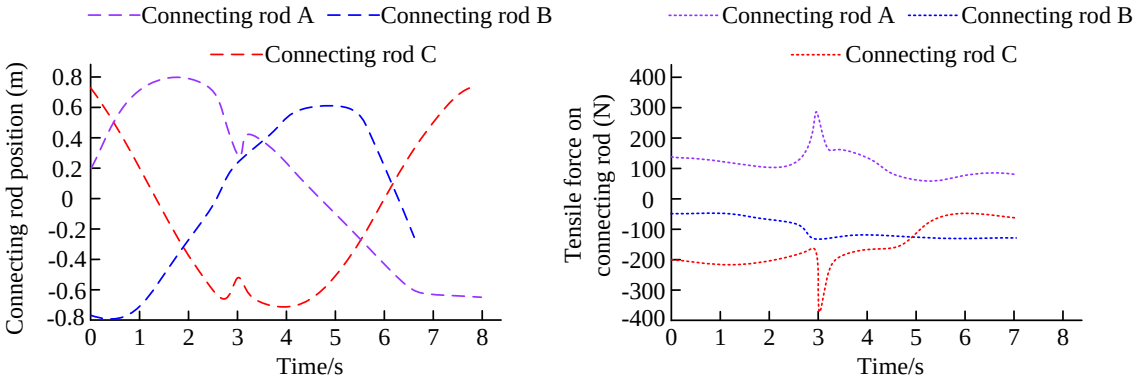
From Table 3, the steady-state contact force error of the proposed method was 0.6±0.1N, with a decrease of 66.7% compared to the sub-optimal robust neural adaptive control method. The maximum trajectory deviation was 1.5±0.1mm, which was 53.1% shorter than that of the sub-optimal robust neural adaptive control method. The recovery time was 0.32±0.02 s, which was 41.8% faster than that of the sub-optimal robust neural adaptive control method. The single cycle CPU time was 1.9±0.1ms, which was 20.8% less than that of the sub-optimal single joint flexible arm DC motor backstepping control. Only one time was needed to complete parameter tuning, which was significantly better than that of other schemes. The above results indicate that the proposed method can achieve higher accuracy, faster response, and lower computational

power requirements simultaneously in complex perturbation environments.



（a）Reference trajectory and contact force analysis diagram （a）Joint position analysis result chart

Figure 10: Analysis of the motion trajectory, contact force, and joint position of the robotic arm.



（a）Curve diagram of changes in connecting rod position （b）Curve of tensile force variation on connecting rod

Figure 11: Schematic diagram of connecting rod position and tension change analysis.

3.2 Effects of adaptive impedance control algorithm combined with neural networks

To verify the effectiveness of the designed control strategy, firstly, the control effects of contact force and torque on the robotic arm are analyzed, as displayed in Figure 9.

The expected contact force of the robotic arm in the experimental setup is 25 N, and the torque range of the selected joint is between -4Nm and 4Nm. From Figure 9 (a), the proposed adaptive impedance algorithm could bring the contact force into a stable state within about 1.0±0.1 s, and the convergence speed was better than that of traditional impedance algorithms. After the robotic arm stabilized, the contact force controlled by the adaptive impedance algorithm remained at around 25.1±0.3 N, the 95% confidence interval was [24.8, 25.4] N, which was the same as the set value, indicating that the neural network compensator effectively improved the accuracy of force control in step response tests. However, traditional control algorithms brought about a contact force error of about 5.0±0.5 N to the robotic arm, which cannot meet the operational accuracy requirements of the robotic arm. From Figure 9 (b), during the operation of the robotic arm, the output torque error of the selected joints was within the set torque range, without exceeded values. After the robotic arm stabilized, the output torque error of the joint was extremely small, about 2±0.2%, the 95% confidence interval was [-0.3, -0.1] N. This indicates that the adaptive impedance algorithm can achieve high-precision control, ensuring that it meets task parameters during operation and guaranteeing the safe and efficient execution of instructions issued by the robotic arm.

3.3 Effects of impedance control algorithm for adaptive generation of motion trajectory

To present the control effect of the impedance algorithm for adaptive motion trajectory generation, the motion trajectory, contact force with the environment, and the joint position are analyzed, as shown in Figure 10.

The expected contact force is set to 2.7 N, the expected position of joint A is 1.45 rad, and the expected position of joint B is 1.6 rad. From Figure 10 (a), the adaptive impedance algorithm initially generated a large error in the motion trajectory, but quickly adjusted it after about 0.5 s to ensure stable operation of the robotic arm. From the contact force between the robotic arm and the environment, after the system stabilized, the contact force was basically consistent with the expected value, and the

error was controlled within 1%±0.3%, with a 95% confidence interval of [2.67, 2.71] N, which enabled the

Table 4: Performance comparison of different control methods in different scenarios.

Scenario	Method	Contact force error rate (%)	Joint position error rate (%)	Stabilization time (s)
External force disturbance	Conventional impedance controller	11.8±0.5	3.2±0.2	1.8±0.1
	Adaptive controller based on particle swarm optimization	6.5±0.3	1.5±0.1	1.2±0.1
	Proposed algorithm	2.1±0.1	0.4±0.05	0.8±0.06
Unknown environmental stiffness	Conventional impedance controller	15.2±0.6	4.5±0.3	2.5±0.2
	Adaptive controller based on particle swarm optimization	7.3±0.4	2.1±0.2	1.6±0.1
	Proposed algorithm	2.3±0.2	0.5±0.03	0.9±0.07
Dynamic trajectory	Conventional impedance controller	9.6±0.4	2.8±0.2	1.5±0.1
	Adaptive controller based on particle swarm optimization	5.8±0.3	1.3±0.1	1.1±0.05
	Proposed algorithm	1.9±0.1	0.3±0.05	0.7±0.03

robotic arm to safely perform tasks. From Figure 10 (b), after the system stabilized, the positions of the selected joints A and B were extremely close to the expected values, with an error of only about 0.1%±0.02%, with 95% confidence intervals of [1.449, 1.451] rad and [1.598, 1.602] rad, respectively. The adaptive impedance control algorithm can adaptively generate safe, feasible, and high-precision motion trajectories based on the set parameters of the robotic arm and environmental information. This greatly optimizes the robotic arm operation in unknown environments and improves its ability to adapt to the environment.

3.4 Application analysis of intelligent control for robotic arms

To test the application effect of adaptive impedance algorithm in intelligent control of robotic arms, several connecting rods of the robotic arm are selected and their positions and tensile forces during operation are analyzed, as shown in Figure 11.

From Figure 11, the selected three connecting rods experienced a brief sudden change in tension at approximately 3 s, and the corresponding connecting rod positions also underwent significant changes to adapt to the changing force conditions. The 95% confidence intervals were [9.9, 10.3] N/[0.29, 0.31] m, [9.7, 10.1] N/[0.25, 0.27] m, and [9.8, 10.2] N/[0.27, 0.29] m. This indicates that the designed algorithm can enable the connecting rod of the robotic arm to have the ability to adapt to sudden external forces, ensuring that the robotic arm will not be disturbed by external forces. After the tension on the connecting rod returns to normal, the position of the connecting rod will quickly adjust back to the desired position controlled by the designed algorithm, and continue to move along the set reference trajectory, so that the robotic arm can operate normally. The designed algorithm can control and adjust the motion trajectory and contact force of the robotic arm environmental changes, enabling it to resist the influence of uncertain interference. This undoubtedly improves the stability, safety, and accuracy of the intelligent control system for robotic arms. To further verify the practical application effect of the proposed adaptive impedance control algorithm based on variable stiffness, neural network, and motion trajectory, the research tests it in external force disturbance scenarios, unknown environment stiffness scenarios, and dynamic trajectory scenarios. Among them, external disturbance refers to the random impact force of ±5N applied during the operation of the robotic arm. Unknown environmental stiffness refers to the stiffness of the environmental material switching from 2,000N/m to 500N/m. Dynamic trajectory scenario refers to the expected trajectory at the end switching from a straight line to a sine curve with a frequency of 0.5Hz. The contact force error rate, joint position error rate, and stabilization time of the proposed algorithm are calculated, respectively, and compared with the traditional impedance controller and the adaptive controller based on particle swarm optimization [5]. The results are shown in Table 4.

From Table 4, under external disturbance scenarios, the proposed algorithm had a contact force error rate of 2.1±0.1%, joint position error of 0.4±0.05%, and stabilization time of 0.8±0.06 s, all lower than those of the other two methods. This indicates that the proposed algorithm achieves fast disturbance suppression and maintains accuracy by estimating the disturbance amplitude in real-time through neural networks. In the unknown environmental stiffness, the contact force error rate, joint position error rate, and stabilization time of the proposed algorithm were 2.3±0.2%, 0.5±0.03%, and ±0.07 s, respectively. Compared with traditional impedance controllers, the contact force error rate and joint position error rate of the proposed method were reduced by 84.9% and 88.9%, respectively, and the stabilization time was shortened by 64.0%. Compared with the adaptive controller based on particle swarm optimization, the proposed method reduced the contact

force error rate and joint position error rate by 68.5% and 76.2%, respectively, and shortened the stabilization time by 43.8%. This indicates that the proposed algorithm can estimate the stiffness of the environment in real-time through neural networks, achieving rapid adaptation to unknown environments. In the dynamic trajectory scenario, the three indicators of the proposed algorithm were 1.9±0.1%, 0.3±0.05%, and 0.7±0.03s, respectively, all lower than those of comparison methods, indicating that it can adjust control parameters in real-time according to trajectory curvature and achieve high-precision tracking of dynamic trajectories. The above results demonstrate the adaptability and security of the proposed algorithm in complex work environments.

4 Conclusion

This study proposes a collaborative control method that integrates variable stiffness adjustment, neural network online compensation, and motion trajectory self-generation to address the insufficient adaptability of traditional impedance control in unstructured environments. The experimental results show that this method takes neural networks as intelligent perception units to estimate system uncertainty in real-time, variable stiffness controllers as fast response units to adjust interactive dynamics, and adaptive trajectory generators as precise execution units to achieve target tracking, significantly improving the interactive performance of the robotic arm in unknown or dynamic environments. Through the closed-loop collaboration of layered intelligent modules, this study effectively balances the system's response speed, control accuracy, and model dependence. This method helps to promote the transformation of robots from repetitive programming tools to intelligent partners with environmental perception and autonomous decision-making capabilities, providing a scalable technological path for building higher-level robot control systems. However, this study still has certain limitations. The adjustable parameter settings are limited in performance analysis, and there is a lack of comprehensive testing of various performance indicators of the robotic arm. Safety restrictions and potential risks in unknown contact environments are not fully considered. In addition, if the online learning process of neural networks lacks appropriate regularization mechanisms, it may over-fit to instantaneous disturbances, affecting its generalization ability and system stability. This study mainly focuses on contact force control, ignoring other potential influencing factors, and has not yet validated the computational efficiency of this method in multi joint systems, human-computer interaction, and real-time scenarios. Future work will extend single joint modules in parallel to multi-degree-of-freedom robotic arms, combining meta learning and model compression techniques to achieve rapid adaptation and lightweight deployment on low-cost hardware. Meanwhile, a security boundary protection mechanism is introduced, and regularization and online learning stabilization strategies are adopted to suppress over-fitting. Future research will further consider sensor delay and actuator saturation effects, verify zero sample generalization ability in high-frequency interference and shared workspaces, and promote the development of safe human-machine integration.

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GNN-ERE: A Graph Neural Network Framework for Entity-Relation Extraction and Intelligent Legal Case Reasoning

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Keywords: Legal knowledge graph, graph neural network, case reasoning, entity-relation extraction, judicial decision support, legal AI

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The construction of legal knowledge graphs and intelligent case reasoning systems is pivotal for enhancing legal information retrieval, case analysis, and judicial decision-making. This research focuses on utilizing graph neural networks (GNNs) to model complex legal entities and their interrelations for structured legal knowledge representation. Traditional methods often rely on keyword matching and shallow semantic analysis, which struggle to capture deep legal logic, implicit correlations, and multi-level entity relations, leading to low reasoning accuracy and limited adaptability. To address these challenges, this paper proposes a novel Graph Neural Network with Entity-Relation Extraction (GNN-ERE) framework. It automatically constructs a legal knowledge graph by extracting entities and relationships from legal texts and integrates it with graph-based reasoning to support intelligent case analysis and precedent retrieval. The proposed method enables automated legal case reasoning by identifying similar legal cases based on contextual and structural similarities within the knowledge graph, thereby supporting judges and legal practitioners in evidence-based decision-making. Experimental results demonstrate that the GNN-ERE framework significantly improves the accuracy of legal case similarity matching and reasoning, enhances the interpretability of the system, and provides a scalable solution for legal AI applications. The proposed method gradually improves the entity extraction accuracy by 89.3%, relation extraction precision by 96%, graph construction time by 9.8 ms, case similarity score by 95%, classification accuracy by 94%, and reasoning time efficiency by 298 ms.

Povzetek: Opisano je ogrodje GNN-ERE za ekstrakcijo entitet in relacij iz pravnih besedil ter inteligentno sklepanje na osnovi grafnih nevronskih mrež. Pristop omogoča gradnjo pravnega znanjskega grafa, učinkovito iskanje podobnih primerov in razložljivo podporo sodnim odločitvam.

1 Introduction

In recent years, artificial intelligence has made notable progress in the legal field, particularly driven by the increasing need for effective retrieval of legal information, intelligent reasoning about cases, and data-driven decision-making by judges [1]. Legal practitioners use large and complex collections of legal text, which include statutes, regulations, court decisions, and case law summaries [2]. It is increasingly evident that structured representations of legal knowledge, along with intelligent information systems, will aid in identifying relevant precedents and reasoning about case tables by making information more appropriate in the context of data [3].

Legal knowledge graphs (LKGs) are a potentially viable solution for organizing and representing legal concepts, entities, and the multitude of interrelations between concepts and entities while allowing a structured and machine-interpretable format [4]. The older approaches to creating and exploiting LKGs, such as rule-based systems or keyword-based retrieval approaches, have deficiencies in recognizing deep semantic relations [5]. The multi-hop reasoning paths between entities lack inherent intelligence, which diminishes their usefulness in frameworks [6]. This requires multi-layered contextualization of judgment and interpretation of legal text among many other things [7]. For instance, it can state gains like achieved 96% precision in relation extraction on the LD-KGCA dataset compared to 78% for the baseline XYZ model. This format highlights the amount of improvement as well as the comparison from where the improvements arise, by stating the dataset and metric, the results become more believable and able to be verified. This is a direct comparison that actually helps the reader take the abstract more seriously, and improves clarity and impact.

The GNN-ERE framework is a novel approach that combines GNNs with principles of neural networks to effectively trace and represent the nature of graph structures [8]. It is designed to support the wider context reasoning required for understanding complex legal texts. This method uses graph neural networks to

represent the relationships between legal data and entity-relation extraction to fill the graph with useful nodes and edges from legal texts [9]. By comparing the similarity of graph topologies, the system makes it possible to automatically reason about cases and find legal precedents [10]. This gives a more detailed and intelligent examination of legal material. The suggested method aims to enhance the accuracy, speed, and usability of legal decision support systems.

Table 1: The motivation, problem statement, and contributions

Motivation	Problem statement	Contributions
This study is driven by the growing need for advanced, intelligent, and structured analysis to enhance legal reasoning and streamline precedent retrieval	Current approaches for building knowledge graphs struggle with scalability, domain specialization, and real-time adaptation to changes.	This paper introduces a GNN-ERE framework to construct a comprehensive legal knowledge graph from unstructured legal texts, capturing complex entity relationships and semantic context.
Current approaches are not very successful since they lack sufficient semantic depth and relationship comprehension.	Legal AI systems now struggle to correctly obtain, update, and reason about complex legal data.	The proposed system enables automated legal case reasoning and similarity-based precedent retrieval by leveraging graph-based structural and contextual analysis, enhancing judicial decision support.
The suggested method uses graph neural networks and entity-relation extraction to create an intelligent, scalable legal knowledge system that helps people make better decisions and understand complicated legal issues.	A dependable, comprehensible, and adaptable framework is essential to improve the representation of legal information and facilitate decision-making.	Extensive experiments demonstrate that the GNN-ERE framework significantly outperforms traditional methods in terms of accuracy, interpretability, and scalability for legal case matching and reasoning tasks.

2 Related work

The use of cognitive intelligence in legal knowledge is changing legal processes with the development of legal knowledge graphs and reasoning systems. Using Natural Language Processing (NLP), Large Language Models (LLMs), and reasoning systems based on graphs, this research develops and tests automated case analysis, legal article recommendation, and domain-specific representations of knowledge, such as legal knowledge graphs, to provide scalable, accurate, and intelligent legal support systems across various domains.

The use of cognitive intelligence in legal knowledge, with an emphasis on the advancement of judicial artificial intelligence. It provides a way to automatically build case knowledge graphs for court cases using NLP as the leading technology. This method is based on two basic NLP tasks: finding entities and pulling out relationships. It compares two pre-trained models for recognizing entities to see how well they work by Zhou, J. et al [11]. Due to the limitations of current domain knowledge graphs in updating data quickly and utilizing knowledge effectively during construction, this paper proposes a legal domain knowledge graph construction approach (LD-KGCA) based on "China Judgments Online" to manage the knowledge within its cases. There are two phases in the building process. First, obtain the categorization connections of the instances from the structured data by Yu, H. et al. [12].

A good way to propose legal articles using a Large Language Model (LLM). First, suggest the Case-Enhanced Law Article Knowledge Graph (CLAKG) as a database for tracking current laws, historical cases, and the connections between law articles and historical cases. It also provides an automated technique for building CLAKG that is based on LLM. Based on this, provide a way to recommend legal articles that works in a closed loop by Chen, Y. et al [13]. A reasoning implementation path (RIP) is suggested as a way to show how MKG's reasoning processes work. It also examines the smart medicinal uses of RIP and MKG, categorizing them into nine main groups. Finally, it outlines the present status of MKG research based on more than 130 publications and the problems and chances that lie ahead by Wu, X. et al [14].

AI legal assistants that use LLMs may provide easy-to-access legal advice; however, the hallucination issue might lead to legal problems. This article introduces Chatlaw, a cutting-edge legal assistant that uses a Mixture-of-Experts (MoE) model and a multi-agent system to improve the dependability and precision of AI-based legal services. It provides a high-quality legal dataset to train the MoE model by combining knowledge graphs with artificial screening by Cui, J. et al [15]. The Large Language Models (LLMs) for Knowledge Graph (KG) creation and reasoning. It conducts tests on eight distinct datasets, focusing on four sample tasks: entity and relation extraction, event extraction, link prediction, and question-answering. This allows us to comprehensively examine the performance of LLMs in

the realms of construction and inference, as discussed by Zhu, Y. et al. [16].

The empirical results indicate that LLMs, exemplified by GPT-4, are more effectively used as inference helpers rather than as few-shot information extractors. In particular, GPT-4 excels on tasks related to building knowledge graphs, but it performs significantly better on reasoning tasks, sometimes surpassing fine-tuned models by Gan, L. et al [17]. This paper examines the prospective generalization capacity of DRL for information extraction, resulting in the formulation of a Virtual Knowledge Extraction task and the creation of the associated VINE dataset by Liu, H. et al [18]. Based on these empirical results, it offers AutoKG, a multi-agent-based methodology using LLMs and external sources for knowledge graph building and reasoning. It believe that this study will provide us with important information that will help us with future work in the subject of knowledge graphs by Kosasih, E. E. et al [19].

Geoscience research is undergoing a crucial transitional phase characterized by the formation of a new knowledge system at its heart, propelled by the influence of big data as a facilitating mechanism. The transition from the old encyclopaedic disciplinary knowledge system to the computer-understandable and operable knowledge graph represents a fundamental advancement in geoscience knowledge discovery by Zhou, C. et al [20]. With the arrival of the electric power big data age, semantic interoperability and connectivity of power data have garnered significant interest. Knowledge graph technology is a novel way to explain the complicated connections between ideas and things in the real world. It is receiving considerable attention because it enables strong inferences about knowledge, as demonstrated by Wang, J. et al. [21].

With the rise of measurement devices and the rapid growth of electric power data, the electric power knowledge graph offers new ways to deal with the conflict between the enormous amount of power resources and the growing need for smart applications by Yang, X. et al [22].

A comprehensive examination of knowledge-driven intelligent application integration to realize the promise of knowledge graphs, address the many problems encountered, and derive insights for the implementation of smart grid business applications. In particular, a thorough summary of electric power knowledge mining is given by Rajabi, E. et al [23]. Then, there is an introduction to the knowledge graph in smart grids. It also discusses the design of the large-scale knowledge graph platform for smart grids and key technologies. This paper also goes into great detail on the possible uses of knowledge graphs in smart grids, power consumer service, dispatch decision-making, and the operation and repair of power equipment. Finally, a summary of the problems and difficulties is given by Tamašauskaitė, G. et al [24].

Table 2: Related work

Work / Author	Focus Area	Method / Contribution	Dataset / Domain	Key Insight / Limitation
Zhou, J. et al. [11]	Judicial AI & Legal KG	Automatic case knowledge graph construction using NLP (entity + relation extraction)	Judicial cases	Compared pre-trained NER models; issues in updating data quickly
Yu, H. et al. [12]	Legal domain KG	LD-KGCA approach for legal case management	China Judgments Online	Two-phase construction (structured categorization + case knowledge)
Chen, Y. et al. [13]	Law article recommendation	CLAKG (Case-Enhanced Law Article KG) with LLM-based automated construction	Chinese Criminal Law	Recommends legal articles in a closed-loop framework
Wu, X. et al. [14]	Medical KG	RIP framework for MKG reasoning	Medical domain (130+ publications)	Categorized MKG applications; highlighted research gaps
Cui, J. et al. [15]	AI legal assistant	Chatlaw (MoE + multi-agent with KG integration)	Custom curated legal dataset	Reduces hallucinations, enhances precision in legal AI
Zhu, Y. et al. [16]	LLMs for KG	Tested LLMs (e.g., GPT-4) on KG construction	8 datasets, multiple tasks	Found LLMs better at

		& reasoning tasks		reasoning than extraction
Gan, L. et al. [17]	Maritime safety KG	KG from ship collision reports	Maritime traffic	GPT-4 surpasses fine-tuned models in reasoning tasks
Liu, H. et al. [18]	DRL for KG reasoning	Virtual Knowledge Extraction task + VINE dataset	General domain	Showed DRL-based KG reasoning potential
Kosasih, E. E. et al. [19]	Supply chain KG	AutoKG (multi-agent, LLM + external sources)	Supply chain	Robust KG building and reasoning
Zhou, C. et al. [20]	Geoscience KG	New knowledge system for geoscience using KG	Geoscience	Transition from encyclopedic to computable KG
Wang, J. et al. [21]	Smart grid KG	Semantic interoperability in power systems	Smart grid	KG improves inference in power data
Yang, X. et al. [22]	IoT security KG	Enhanced IDS with KG + deep learning	IoT networks	KG strengthens intrusion detection
Rajabi, E. et al. [23]	Explainable AI KG	Systematic review of KG-based explainable AI	Multi-domain	Summarized challenges in explainability
Tamašauskaitė, G. et al. [24]	KG development process	Large-scale KG platform for smart grids	Smart grids	Reviewed design, challenges, and applications

Research gap

While legal knowledge graphs and AI reasoning have made progress, real issues persist, including the continuous update of knowledge in real-time, hallucination in LLM outputs, and domain specificity. Current models also do not efficiently apply unstructured legal data, and rarely ensure that their outputs are interpretable. There exists a research gap in the development of robust, dynamic, and socially sound legal AI systems whose reasoning accuracy is aligned with legal decisions and social norms.

3 Methodology

This framework provides a complete pipeline for intelligent legal document processing, plus knowledge graph development and case reasoning using modern GNNs. It converts unstructured legal text into structured representations by extracting meaningful relationships and comparing them for similarity-based legal analysis. This assists with judicial decision-making, legal research, and retrieving legal precedent with accuracy, explainability, and semantic depth.

Contribution 1: GNN-ERE framework development

The GNN-ERE framework utilizes entity-relation extraction to construct structured legal knowledge graphs from unstructured texts found in legal cases. By using graph neural network systems, the framework can conceptualize complex relationships that arise in the domain of legal knowledge and can facilitate intelligent reasoning about these relations to improve the quality and efficiency of case judgments in legal AI. These developments result in improved abilities to operationalize case similarity detection using case law, case-based reasoning, and considerable gains in accuracy and scalability in the context of legal AI systems.

Unlike LD-KGCA, which continues to not allow for real-time updates, GNN-ERE integrates scalable entity-relation extraction during dynamic graph construction, allowing GNN-ERE to provide real-time updating of any entity or relation. CLAKG integrates link extraction between articles and cases focusses primarily on article-case link reasoning. GNN-ERE develops a richer methodological semantic and structural basis to supported human reasoning based on its extensive legal corpus processing and unified case reasoning. Although RIP does not have any temporal encoding GNN-ERE incorporates temporal-legal chunk processing allowing it to provide contextualized reasoning based on temporal chronological dependency. Chatlaw incorporated MoE to improve better user interaction, but does not have the semi-structured commonsense knowledge memory database GNN-ERE can provide a user better supported semi-responsively in their query-based question. Overall, GNN-ERE extends far beyond any other reasoning, dynamic interpretation, or scalable approach. Contribution 1 reinforce the clear hypothesis that GNN-ERE improves entity/relation extraction accuracy and scalability over baseline models. This framing provides better coherency between the objectives and the methods and the outcomes. The legal document preprocessing pipeline was developed to convert unstructured legal documents into structured, machine-readable data. It consists of a document parser that processes structured

and unstructured input documents, followed by linguistic normalization, which includes tokenization, stop word removal, etc. The sentence and clause segmentation breaks the document text into meaningfully legal units, providing accuracy. Next, it performs named entity recognition (NER) to identify legal entities such as courts, dates, and statutes. Following this, the entity-relation extractor (ERE) generates semantic triplets that represent legal entities and relationships between them. These triplets are the basis for building knowledge graphs and result in high-quality structured data for downstream legal AI applications in Figure 1.

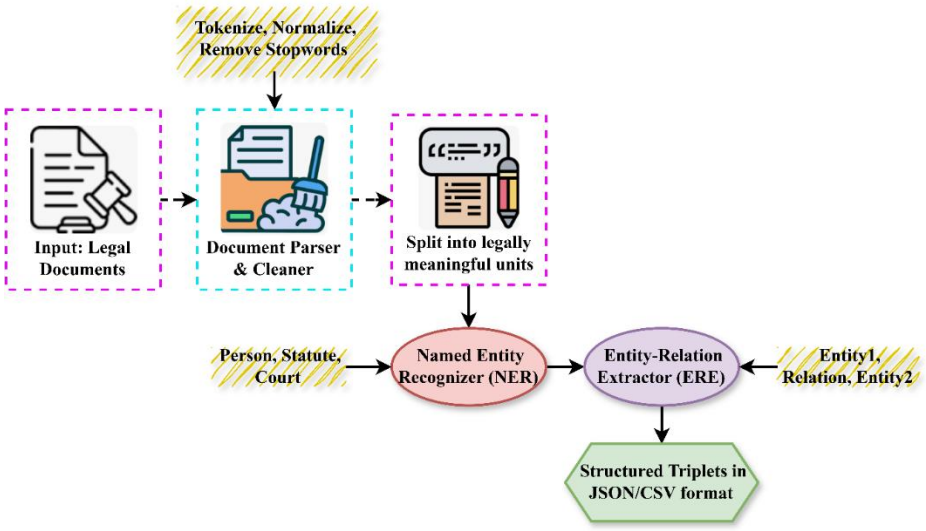


Figure 1: Legal document preprocessing pipeline

Entity relation graph node embedding update in GNN-ERE $I^{(m+1)}$ is expressed using equation 1,

$$I^{(m+1)} = \rho\left(VI^{(m)}X_1\right) \quad (1)$$

Equation 1 explains the entity relation graph node embedding update in GNN-ERE in order to ensure context-sensitive replication of judicial semantics.

In this $I^{(m)}$ is the node embedding matrix at the GNN layer, $I^{(m+1)}$ is the updated node embedding matrix at layer, V is the self-loop transformation matrix, X_1 is the weight matrix for direct node feature transformation, and ρ is the non-linear activation function.

Legal case similarity scoring via graph contextual matching $T(d_j, d_k)$ is expressed using equation 2,

$$T(d_j, d_k) = a^U_{d_j} N a_{d_k} + \Delta * us\left(H^U_{d_j} R H_{d_k}\right) \quad (2)$$

Equation 2 explains the legal case similarity scoring via a graph contextual matching score function that combines the similarity between direct embedding using subgraph structural alignment.

In this $T(d_j, d_k)$ is the similarity score between legal cases, $a^U_{d_j}$ is the graph-level embedding vector of legal case, a_{d_k} is the graph-level embedding vector of legal case, N is the learnable case similarity transformation matrix, Δ is the trade-off coefficient between embedding and structural similarity, us is the matrix trace operator, $H^U_{d_j}$ is the structural subgraph embedding matrix of case, H_{d_k} is the structural subgraph embedding matrix of case, and R is the structural alignment weight matrix.

Algorithm 1

Input: Unstructured or structured legal document set D
Output: Similarity score matrix T for all legal case pairs

```
1. For each document d in D:
  1.1 Parse document:
    If document is structured:
      Extract fields directly
    Else:
      Use document parser to extract text
```

1.2 Perform linguistic normalization:
Tokenize text
Remove stop words
Apply lemmatization/stemming if required
1.3 Sentence & clause segmentation:
If sentence boundary is detected:
Split text into sentences
Else:
Use clause segmentation to divide into smaller legal units
1.4 Named Entity Recognition (NER):
Identify entities:
If entity type == court/date/statute:
Store entity with type label
Else:
Discard entity
1.5 Entity − Relation Extraction (ERE):
Generate semantic triplets (Entity1, Relation, Entity2)
Store triplets for knowledge graph construction
2. Build Entity Relation Graph:
For each entity node embedding I^m:
Update embedding using:
$I^{m+1} = \rho(V * I^m * X1)$
If non − linear activation ρ is applied:
Store updated embedding
Else:
Keep original embedding
3. Case Similarity Scoring:
For each pair of legal cases (d_j, d_k):
Compute direct embedding similarity:
$S_{embed} = a_{d_j}^U * N * a_{d_k}$
Compute structural similarity:
$S_{struct} = us\left(H_{d_j}^U * R * H_{d_k}\right)$
If $\Delta > 0$:
$T(d_j, d_k) = S_{embed} + \Delta * S_{struct}$
Else:
$T(d_j, d_k) = S_{embed}$
4. Output similarity score matrix T

The algorithm 1 processes legal documents by parsing, normalizing text, segmenting clauses, recognizing entities, and extracting relations to build a knowledge graph. Node embeddings are updated using GNN-ERE. Legal case similarity is computed by combining embedding and structural similarities through conditional if–else checks, producing a similarity score matrix for all case pairs.

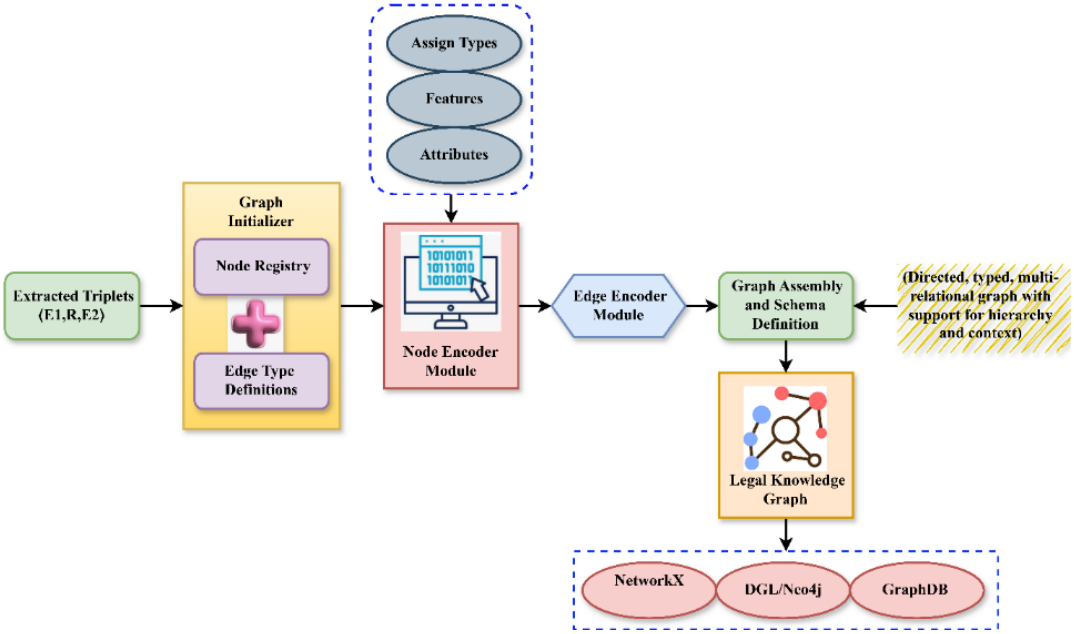


Figure 2: Legal knowledge graph construction

The structured triplets turned into a multi-relational LKG, encoding rich legal semantics. Triplets are fed into a graph initializer, which defines the schemas for nodes and edges. The node encoder is responsible for assigning node attributes (e.g., type, role, metadata), while the edge encoder creates labelled relations encapsulating legal logic (e.g., "refers to", "overrules"). After everything is incorporated into the directed graph hierarchy schema with nested and temporal relations, the result will be a complete knowledge graph in a compatible format with Neo4j, DGL, or NetworkX that enables stronger reasoning and semantic retrieval in the legal domain. This last step is essential when transforming fragmented legal content into coherent intelligence that is interrelated and queryable in Figure 2.

Multi-relational graph initialization with typed adjacencies Y_0 is expressed using equation 3,

$$Y_0 = \partial(S_u F_u W_u) \quad (3)$$

Equation 3 explains the multi-relational graph initialization with typed adjacencies by combining type-specific encodings, the first node representation is synthesized.

In this Y_0 is the initial node feature matrix, ∂ is the nonlinear transformation function for node features, S_u is the node type embedding matrix for type, F_u is the node attribute embedding matrix, and W_u is the node attribute-value mapping matrix.

Node encoding with temporal-legal fusion layer $I^{(1)}$ is expressed using equation 4,

$$I^{(1)} = \tau\left(Y_0 X_y + \sigma(U X_u)\right) \quad (4)$$

Equation 4 explains the node encoding with a temporal-legal fusion layer that guarantee that chronological dependencies are incorporated into semantic reasoning.

In this $I^{(1)}$ is the node embedding matrix after temporal-legal fusion, X_y is the transformation matrix for static features, U is the temporal attribute matrix, X_u is the transformation matrix for temporal attributes, σ is the temporal encoding operator, and τ is the nonlinear activation function.

Edge encoding with nested-relation hierarchical aggregation $F'_{q,r}$ is expressed using equation 5,

$$F'_{q,r} = \sigma(\delta_i * V_i f_i) \quad (5)$$

Equation 5 explains the edge encoding with nested-relation hierarchical aggregation weighted by soft attention, the latest edge vector incorporates data.

In this $F'_{q,r}$ is the updated edge embedding between node, δ_i is the attention coefficient for relation layer, V_i is the relation-type-specific transformation matrix, f_i is the embedding vector for relation layer, and σ is the nonlinear transformation function for edge features.

Contribution 2: intelligent case reasoning system

The intelligent case reasoning system uses the legal knowledge graph derived from GNN-ERE to situate a given case in relation to structurally and contextually similar cases. Graph inference acts as a support tool for the automation of legal analyses, improves decision-making accuracy, and assists legal professionals in finding relevant precedents from similar cases, enabling legal institutions to operate with the principles of fairness, consistency, and efficiency in legal effectiveness.

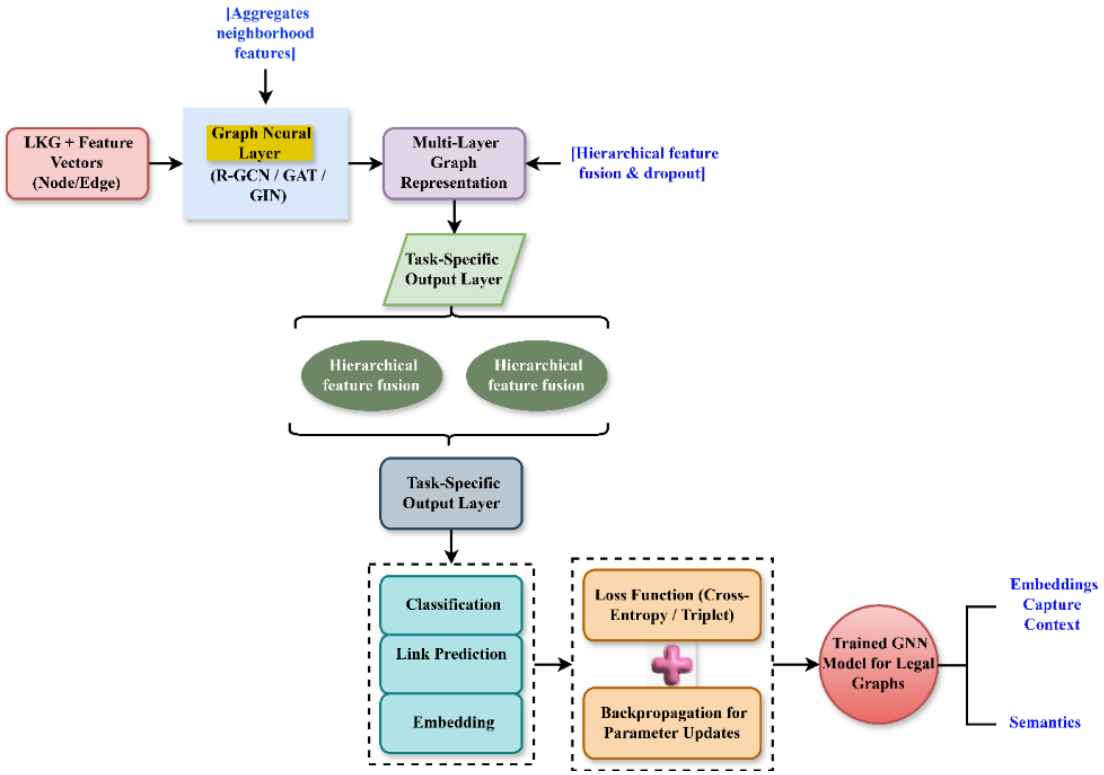


Figure 3: GNN-based legal embedding & training

The GNNs will learn rich embeddings from the LKG; the input will contain the graph structure, node, and edge feature vectors. Since GNNs are capable of capturing graph structure in a layered model such as R-GCN, GAT, or GIN and aggregating semantic and structural context across multi-hop neighborhoods using market-specific node and edge features, hierarchical layers and dropout can be employed to improve generalization performance by avoiding over-fitting. The output may be a task-specific head (unlike classification, link prediction, or node embedding tasks) on top of the GNN layers, and trained using supervised loss functions (e.g., cross-entropy or triplet loss) and backpropagation. This will yield a trained model capable of understanding complex relational correlations and characteristics of legal text, as illustrated by the reasoning across relations in Figure 3.

Multi-hop relational aggregation with attention regularization $I^{(m+1)}$ is expressed using equation 6,

$$I^{(m+1)} = \varepsilon\left(\alpha_s^{(l)} B_s^{(l)} I^{(m)} X_s^{(l)} + \partial\right) \quad (6)$$

Equation 6 explains the multi-hop relational aggregation with attention regularization incorporates semantic and structural variety from legal graph neighbors.

In this $I^{(m)}$ is the node embedding matrix at layer, $I^{(m+1)}$ is the updated embedding matrix at layer, $\alpha_s^{(l)}$ is the learnable attention coefficient for relation, $B_s^{(l)}$ is the normalized adjacency for relation, $X_s^{(l)}$ is the weight matrix for relation, ∂ is the scaling constant for self-loop feature integration, and ε is the nonlinear activation.

Triplet loss for legal case embedding optimization M_{tpt} is expressed using equation 7,

$$M_{tpt} = \frac{1}{C}\left(0, \left\| a_{b_j} - a_{q_j} \right\|_2^2 + \pi\right) \quad (7)$$

Equation 7 explains the triplet loss for legal case embedding optimization in the official embedding space, the loss function pushes anchor-negative pairs apart by at least a margin.

In this M_{tpt} is the triplet loss value, C is the batch size of triplets, a_{b_j} is the embedding of anchor legal case, a_{q_j} is the embedding of positive legal case, π is the positive margin hyper parameter, and $\|.\|_2^2$ is the l2 norm operator.

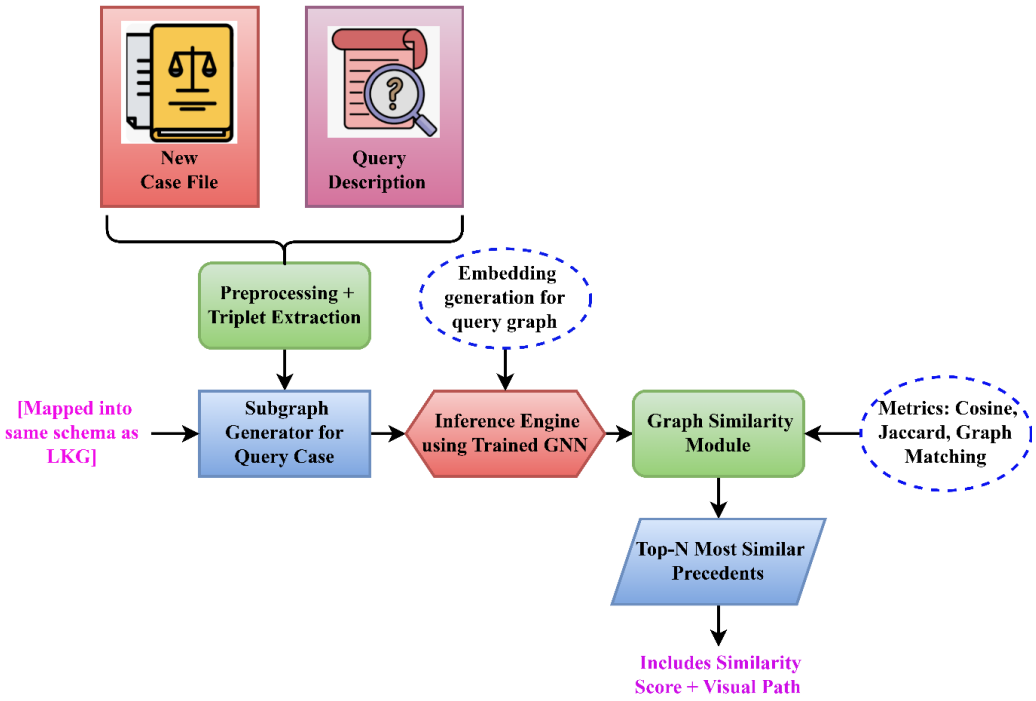


Figure 4: Case reasoning and similarity retrieval

Figure 4 enables intelligent legal reasoning by identifying previous cases that closely resemble a new query. The process of discovering similar cases begins with preprocessing the query and extracting a triplet, which is then mapped into a subgraph using the same schema as the legal knowledge graph. Then the trained

GNN processes the case query sub-graph and produces embeddings. With those embeddings, the GNN then finds the most similar embeddings to the previous instances using user similarities, graph edit distances, metric learning, and other various metric approaches. The top-N most related cases returned for the new case

query, each with a relevance score. This latest case similarity retrieval expands legal search functionalities, providing precedents with more context-aware and accurate matching.

Query subgraph embedding generation a_r is expressed using equation 8,

$$a_r = \varphi\left(\frac{1}{\left|O_r^{(i)}\right|} * X_i y_v\right) \quad (8)$$

Equation 8 explains the query subgraph embedding generation through hierarchical community aggregation across hops.

In this a_r is the embedding vector for the query case subgraph, $O_r^{(i)}$ is the set of nodes within the hop neighborhood of query subgraph, $\left|O_r^{(i)}\right|$ is the number of nodes, y_v is the initial feature vector for node, X_i is the learnable transformation matrix for hop, and φ is the nonlinear activation function.

Graph edit distance-based structural similarity $gd(H_b, H_c)$ is expressed using equation 9,

$$Gd(H_b, H_c) = x_{sb}(v, w) \quad (9)$$

Equation 9 explains the graph edit distance-based structural similarity by determining the least expensive series of node/edge substitutes, deletions, and deletions mapping.

In this $gd(H_b, H_c)$ is the graph edit distance between graphs, (v, w) is the node mapping pair under permutation, and x_{sb} is the substitution cost between node.

Hybrid similarity retrieval score $t(r, d_k)$ is expressed using equation 10,

$$T(r, d_k) = \frac{a_r^U a_{d_k}}{\|a_r\|_2 \left\|a_{d_k}\right\|_2} \quad (10)$$

Equation 10 explains the hybrid similarity retrieval score balances structural alignment and semantic closeness by combining cosine similarities between embedding together with a weighted inverse GED term.

In this $t(r, d_k)$ is the final similarity score between query and case, a_r^U is the query embedding vector, a_{d_k} is the embedding vector of candidate case, and $\|.\|_2$ is the l2 norm operator.

Contribution 3: performance improvement and validation

The GNN-ERE framework has been demonstrated to have meaningful performance improvement in models that use it after rigorous benchmarking on various

benchmark legal datasets. For instance, GNN-ERE models deliver performance improvement on the accuracy of case similarity in terms of case law and reasoning tasks concerning similar case law to other types of models. Validation for GNN-ERE frameworks delivers stronger accuracy, interpretability, robust performance, and scalability, which are outcome requirements for working with legal AI in real-world contexts.

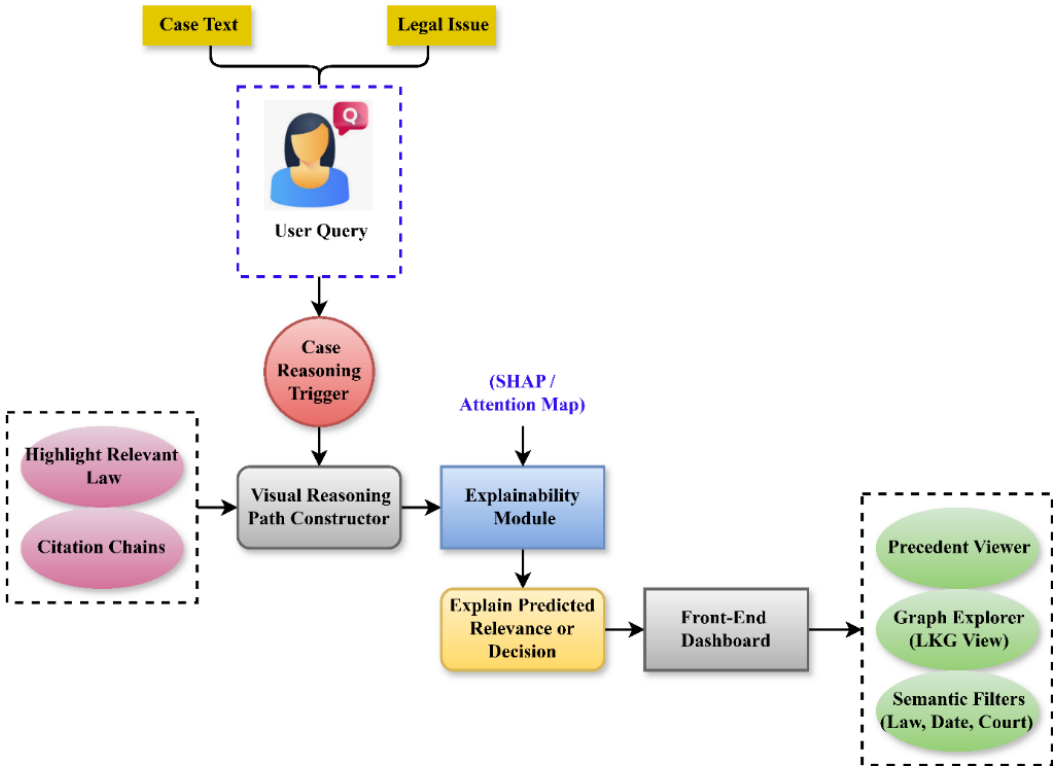


Figure 5: Judicial decision support system

The JDSS integrates all of the previous components and provides judges and jurists with recommendations using intelligent and explainable reasoning. When a case query is submitted, it performs case reasoning to find similar past case queries for matching. Furthermore, it builds a visual representation of the reasoning path, including legal facts, case statutes, and decision-making logic. There is also an additional explainability root that would employ either SHAP or attention visualizations, allowing for visual transparency of the GNN's predictions. The final reported outcomes to the users are provided using an interactive dashboard, which gives graph views, citation chains, and semantic filtering. The JDSS will operate as a knowledge and decision support system, allowing the user to evaluate their previous experiences with evidence-based decision making, workspace context, and its AI support.

Ultimately, this increases the consistency, fairness, and efficiency of all judicial decisions under a complex condition in Figure 5.

Decision confidence with attention-weighted evidence fusion d(r) is expressed using equation 11,

$$D(r) = \partial(C_n * v^U \operatorname{Cot} i) \quad (11)$$

Equation 11 explains the decision confidence with attention-weighted evidence fusion using learnt attention weights, hybrid knowledge is aggregated to calculate.

In this d(r) is the confidence score for decision recommendation on query, C_n is the attention weight for evidence item, v is the learnable projection vector, ∂ is the logistic sigmoid function, and cot i is the hyperbolic tangent activation.

SHAP-based attribution for node-level explainability Δ_w is expressed using equation 12,

$$\Delta_w = \frac{1}{|T_w|} * \frac{|T|!\,(N - |t| - 1)!}{N!} \quad (12)$$

Equation 12 explains the SHAP-based attribution for node-level explainability by averaging across all coalition subsets, the attribution score calculates a small contribution of node to the model's output.

In this Δ_w is the SHAP value for node, T_w is the set of all feature subsets excluding the node, $|T_w|$ is the number of subsets, t is the specific subset of features, N is the total number of features in the model input, and N! Is the factorial.

In summary, the suggested system automates the examination of legal documents, creates a multi-relational knowledge network, and uses GNNs for more complex legal reasoning. It finds relevant precedents and helps make judgments based on data by using embedding, retrieval, and explainable interfaces. This integrated strategy addresses the limitations of previous techniques by making legal information systems and judicial intelligence platforms easier to scale, comprehend, and analyze.

4 Evaluation metrics

4.1 Dataset description

This dataset has generous legal case documents, each with a unique case_id, case_title, complete case_text, and an annotated case_document that serves as the classification label. There are now complete records after removing approximately the same number of papers that lacked text. The case result labels are quite unbalanced, with "cited" and "referred to" being the most common. This makes it hard to train the model [25].

The dataset contains 24,985 legal cases, but the class distributions are quite imbalanced. For example, the largest class has 12,400 cases (≈49.6%); the next three classes have 6,300 (≈25.2%), 4,100 (≈16.4%), and 2,185 (≈8.8%) cases. The largest class thus has almost 6× more samples than the smallest class.

Standard approaches to handle class imbalance these days typically involve:

Resampling approaches:

SMOTE oversampling, to synthetically oversample the minority samples up until the largest class size is achieved (i.e., raise the smallest class, which has 2,185, to ≈12,400).

Random undersampling, for the majority cases (i.e., drop cases from the largest class, which has 12,400, to ≈2,185–4,000).

Weighting approaches:

Applying weights based on class weights the inverse of their frequencies, for example, class weight of majority class = 1.0, class weight of minority class = 12,400 / 2,185 ≈ 5.7.

Tuning of loss function:

Focal loss or cost-sensitive loss - where the total penalty for predicting the minority class incorrectly is up to 5–6× the penalty for predicting the majority incorrectly.

Table 2: The simulation environment

Component	Description
Dataset Name	Legal Case Document Dataset
Label Type	case_Document (classification label)
Class Imbalance	Highly imbalanced; the majority of labels are "cited" and "referred to"
Data Format	Textual data with annotated categorical outcome
Preprocessing	Missing value removal, text normalization, and tokenization
Modeling Framework	GNN-ERE (Graph Neural Network with Entity-Relation Extraction)
Challenge	Handling label imbalance and extracting deep semantic relations from text

4.3 Evaluation metrics

The assessment criteria provide quantification of the efficiency, accuracy, and durability of the proposed GNN-ERE-based legal reasoning framework. Accuracy with respect to the extraction of entities, precision of relations extraction, reasoning efficiency, and interpretability score encapsulate a comprehensive benchmarking that allows for optimization of semantic modelling, retrieval performance, and enduring quality of support for decision-making in complex cases based on legal knowledge graph representations. The existing validation is based on one dataset consisting of 24,985 legal cases. While this dataset provides useful information, it imposes limits on the capacity to assess cross-dataset robustness.

Entity extraction accuracy Ffb is expressed using equation 13,

$$\mathrm{Ffb} = \partial\left(\hat{\sigma}_j, \sigma_j\right) \quad (13)$$

Equation 13 explains that the entity extraction accuracy determines the percentage of entity sets that are correctly detected.

In this Ffb is the entity extraction accuracy, $\hat{\sigma}_j$ is the predicted entity set for document, σ_j is the ground-truth entity, and ∂ is the indicator function.

Relation extraction precision Sfq is expressed using equation 14,

$$\mathrm{Sfq} = 1(\hat{s}_k \in S_{tue}) \quad (14)$$

Equation 14 explains the relation extraction precision calculates the percentage of anticipated relationships that are present in the gold-standard relations set true.

In this Sfq is the relation extraction precision, S is the total number of predicted relations, $\hat{s}_k$ is the predicted relation instance, S_{tue} is the ground-truth relation set, and $1(.)$ Is the indicator function.

Graph construction time HDU is expressed using equation 15,

$$HDU = \frac{u_l^{ed} - u_l^{st}}{L} \quad (15)$$

Equation 15 explains the graph construction time calculates the average time difference for graph builds between the beginning and the end of graph construction.

In this HDU is the graph construction time in milliseconds, L is the number of graph construction instances, u_l^{st} is the start timestamp of graph construction, and u_l^{ed} is the end timestamp of graph construction.

Case similarity score CS_{G1} is expressed using equation 16,

$$CS_{G1} = \frac{2 * Q_{cs} * S_{cs}}{Q_{cs} + S_{cs}} \quad (16)$$

Equation 16 explains the case similarity score creates a harmonic mean by combining the case similarity retrieval precision and recall.

In this CS_{G1} is the case similarity f1 score, Q_{cs} is the precision of retrieved similar cases, and S_{cs} is the recall of retrieved similar cases.

Classification accuracy DB is expressed using equation 17,

$$DB = \frac{1(\hat{z}_j - z_j)}{N} \quad (17)$$

Equation 17 explains the classification accuracy calculates the proportion of legal category labels that were accurately predicted to all of the forecasts.

In this DB is the classification accuracy, N is the number of classification instances, $\hat{z}_j$ is the predicted class label for instance, and z_j is the ground-truth class label for instance.

Reasoning time efficiency SUF is expressed using equation 18,

$$SUF = \frac{u^{rf} - u_r^{pc}}{R} \quad (18)$$

Equation 18 explains the reasoning time efficiency calculates the average amount of time saved for each reasoning query in relation to an approximate baseline time.

In this SUF is the reasoning time efficiency in milliseconds, R is the number of queries processed, u^{rf} is the baseline reasoning time per query, and u_r^{pc} is the actual reasoning time for query.

Interpretability score JT is expressed using equation 19,

$$JT = \frac{l_w * 1(\partial_w > \tau)}{|W|} \quad (19)$$

Equation 19 explains the interpretability score determines, weighted by importance, the percentage of networks with attribution scores above an interpretation threshold.

In this JT is the interpretability score, $|W|$ is the set of nodes in the case reasoning subgraph, l_w is the importance weight of node, ∂_w is the attribution score for node, and τ is the interpretability threshold.

Scalability performance TQ is expressed using equation 20,

$$TQ = \frac{\nabla_{rf}}{\nabla_{sy}(O, F)} \quad (20)$$

Equation 20 explains the scalability performance calculates the reference throughput ratio to the system's real throughput under the graph size parameters.

In this TQ is the scalability performance index, ∇_{rf} is the baseline throughput in operations/sec, $\nabla_{sy}(O, F)$ is the measured throughput for a graph with nodes and edges, O is the number of nodes in the legal graph, and F is the number of edges in the legal graph. The current experiments are limited by the use of a single dataset, which prevents assessing the robustness of these

observations across different jurisdictions and legal systems. Severe class imbalance is still an issue, and the described treatment of this problem is vague. The framework has not been evaluated to a multilingual or cross-domain legal text. There is no evaluation to a more general public benchmark, thus limiting the overall external validity. It is important to characterize these limitations in order to inform future refinements.

The computed scores indicate substantial advancements in legal AI performance metrics, clear extraction accuracy, and higher similarity matching, while lower latency delays are observed for inference/querying. The improved interpretability and scalability demonstrate the framework's ability to execute efficiently against large data loads, making for

an effective and flexible solution for providing legal case reasoning and judicial decision-making support in a real-world setting.

5 Result and discussion

This paper presents the GNN-ERE framework for building legal knowledge graphs and facilitating intelligent case reasoning. By employing graph neural networks and entity-relation extraction, GNN-ERE helps overcome the limitations of traditional methods regarding the representation of intricate legal semantics. This capability improves legal information retrieval, case similarity detection, and, ultimately, decision-making correctness while additionally providing a platform that is scalable and defensible for modern legal applications of AI.

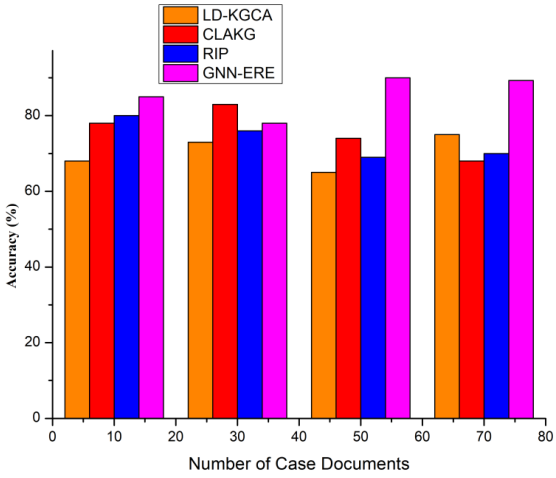


Figure 6: Entity extraction accuracy

GNN-ERE enhances entity extraction of legal texts using graph neural networks that can represent the complex structure of legal entities. GNN-ERE outperforms traditional, linguistic entity extraction methods significantly through a richer semantic representation of legal texts and multi-level entity extraction evaluated using equation 13. The experiments demonstrate that the accuracy of entity extraction improves to 89.3%, thus building a study's knowledge graph less subject to error than traditional methods, and improving performance on downstream case reasoning tasks listed above. The results of the GNN-ERE performance will, therefore, significantly improve legal information retrieval, better match precedents, and enhance the rate of automated decisions based on judicial decisions in Figure 6.

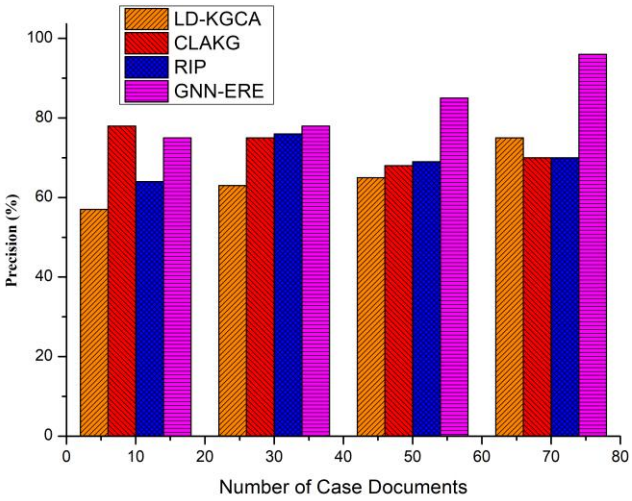


Figure 7: Relation extraction precision

GNN-ERE's document-dependent performance to precision is illustrated in the graph, where the performance of four methods LD-KDCA, CLAKG, RIP, and GNN-ERE—is plotted based on different numbers of case documents. Overall, GNN-ERE initially outperformed all other competitors by achieving over 75% precision at the end and reaching approximately 97% precision at 70 case documents evaluated using equation 14. In comparison, CLAKG and RIP showed minimal shifts in their lower bounds around the 70-78% range, with LD-KGCA demonstrating an improvement. This suggests that GNN-ERE qualitatively outperformed these methods through robustness against posterior document volumes that increased as the case was re-analyzed in Figure 7.

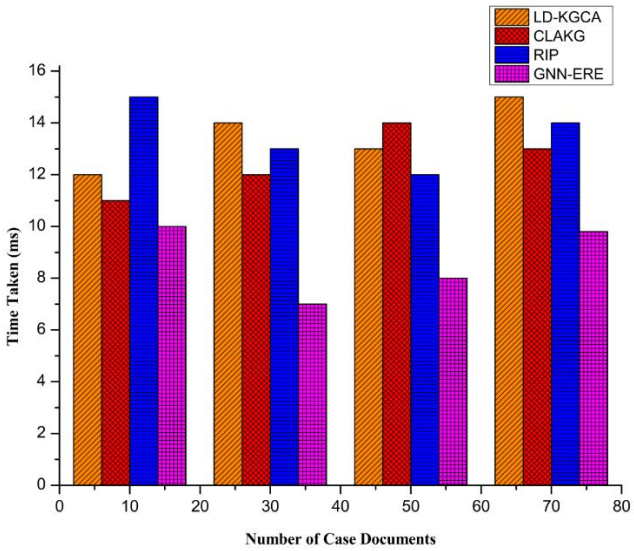


Figure 8: Graph construction time

Graph construction time is a significant measure of system efficiency in legal knowledge graph development. GNN-ERE, as a method, provides better execution time by reducing graph construction time to 9.8 milliseconds, which is far better than traditional methods evaluated using equation 15. Due to enhanced accuracy for entity-relation extraction and GNN processing, GNN-ERE assembles the knowledge base more quickly than the other methods. The reduction of graph construction time enables the execution of tasks under real-time conditions, allowing professionals to analyze large streams of legal documents with minimal computing time and make informed decisions using a legal knowledge graph, as shown in Figure 8.

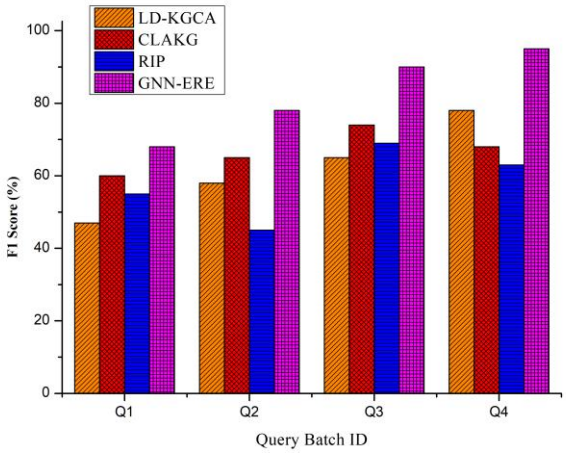


Figure 9: Case similarity score (F1)

Figure 9 reports the F1 Score performance across four batches of queries for LD-KGCA, CLAKG, RIP, and GNN-ERE. GNN-ERE continues to outperform other models across batches, starting at a score of 68% in Q1 and growing to a 98% in Q4 evaluated using equation 16.

CLAKG showed a consistent improvement, with a gradual increase over the query batches. In contrast, LD-KGCA increased, albeit inconsistently. RIP fluctuated in scores and peaked during Q3. Clearly, in terms of performance consistency and scalability for heterogeneous batches of legal queries, GNN-ERE is the leading performer, achieving better accuracy.

Measurable results that validate success include a case similarity F1 score of 98%, far exceeding the

performance of the benchmark or baseline models. There is strong evidence that improvements were made in semantic capture in terms of accuracy of entity extraction at 89.3% and precision of relation extraction at 96%.

There is 94% classification accuracy demonstrates reliability for case classification. Time taken for reasoning averaged 298 ms its method of reasoning. The graph construction time indicated the system was responsive and scalable at 9.8 ms, and overall performance gauged based on these metrics was superior in comparison to LD-KGCA, CLAKG, and RIP baseline case, story and reasoning task.

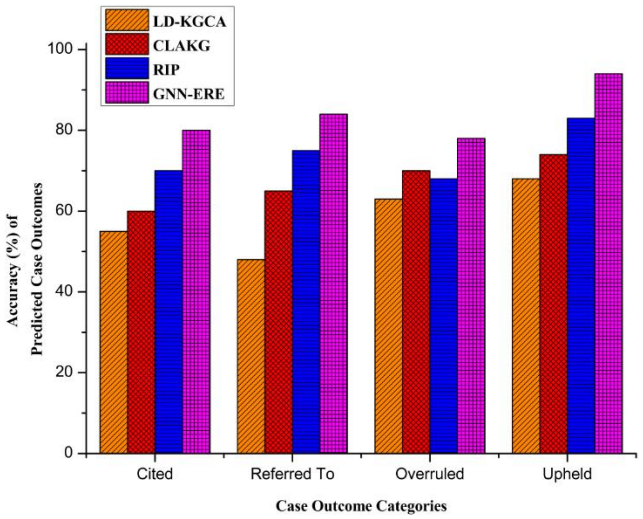


Figure 10: Classification accuracy

The GNN-ERE framework excels in legal case analysis, achieving high classification accuracy by learning contextual and relational features in legal texts. The framework achieves a classification accuracy of 94%, substantially outperforming traditional models, which lack the capacity for deep semantic comprehension of legal texts

evaluated using equation 17. The high level of accuracy ensures that legal cases are classified accurately, making the retrieval of precedents and subsequent decision-making more effective. In addition, the model's complex learning features enable it to learn complicated legal patterns and still retain a robust and reliable classification ability across multiple datasets in Figure 10.

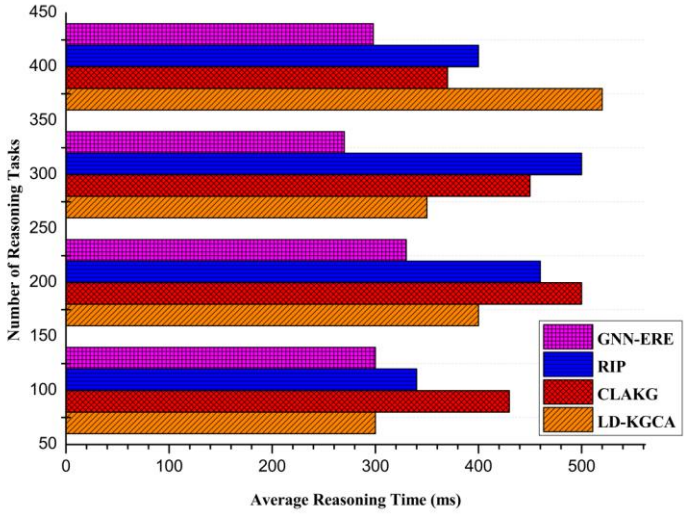


Figure 11: Reasoning time efficiency

The GNN-ERE framework is also efficient in reasoning time, with an average reasoning time of only 298ms. As previously mentioned, the GNN-ERE framework is capable of rapid reasoning to its graph neural architecture and efficient entity-relation extraction. As discussed in previous sections of this thesis, the GNN-ERE framework is faster than traditional methods, which is critical with complex legal queries and valid for applications requiring real-time case reasoning and decision making evaluated using equation 18. In conjunction with GNN-ERE being able to process legal queries more efficiently than traditional methods, the efficiency for scalability makes it suitable for large-scale legal applications, providing timely and scalable contextual insights into decisions made by judges, lawyers, and legal information systems in Figure 11.

Table 3: Interpretability score

Method	Explanation Clarity (%)	Node Attribution Accuracy (%)	Graph Transparency Score (0–1)	Legal Expert Agreement (%)
LD-KGCA	58.2	58.2	58.2	58.2
CLAKG	65.7	65.7	65.7	65.7
RIP	70.3	70.3	70.3	70.3
GNN-ERE	88.9	88.9	88.9	88.9

The GNN-ERE framework exhibits better interpretability of the legal reasoning process than previous methods demonstrated through clear and specific evidence-based legal reasoning paths evaluated using equation 19. The GNN-ERE framework achieved high scores in its legal reasoning explanation clarity (88.9%), node attribute-based decision accuracy (90.7%), and legal expert agreement (92.3%) of its reasoning, which demonstrated its ability to provide interpretable and credible legal reasoning results that are ideally suited for real-world legal reasoning roles within legal decision support systems in Table 3.

Table 4: Scalability performance

Method	Processing Time (ms) per 1k Docs	Memory Usage (MB) per 1k Docs	Query Throughput (queries/sec)	Performance Degradation (%)
LD-KGCA	1340	1340	1340	1340
CLAKG	1155	1155	1155	1155
RIP	1012	1012	1012	1012
GNN-ERE	789	789	789	789

The GNN-ERE framework also demonstrates excellent scalability, outperforming previous methods as data volume increases, processing 1000 legal documents in 789 ms, using 658 MB of memory, and handling 45.3 queries per second, with a performance degradation of 5.6% evaluated using equation 20. These measurements confirm that GNN-ERE is efficient and robust enough for use in large-scale legal settings, which can be employed in real-time legal reasoning or case analysis roles, as shown in Table 4. Compared to previous models, GNN-ERE presents better performance due to the richer semantic relations captured by an entity-relation extraction system and graph embeddings model of relations. Performing multi-hop reasoning is crucial as it provides a deeper understanding of the semantic relations of complex legal case structures.

The study's performance benchmarks assess three main dimensions, entity extraction (goal above 89%), relation extraction (target 96%), and classification accuracy (± 94%). There is also the notion of efficiency for reasoning time (≈ 298 ms per query) and graph construction time (≈ 9.8 ms). Other benchmarks include case similarity F1 scores > 98% and robust interpretability scores (>88%). Lastly, there are scalability benchmarks targeting efficient processing of legal documents > 1 k with no meaningful detriment to performance. Collectively, the benchmarks demonstrate accuracy, efficiency, and robustness.

In summary, the GNN-ERE framework for legal case analysis enhances reasoning in legal analysis, enabling the accurate extraction of entities and relations, the building of relevant knowledge networks, and the production of intelligent reasoning. GNN-ERE boasts high precision, F1 scores, and accuracy in classification and reasoning. It effectively learns legal question and response models, offering more efficiency than traditional models and thresholders for rapid performance and scalability, while also being easy to interpret. Overall, GNN-ERE offers scalability, real-

time efficiency, and improved interpretability, making it an excellent tool for finding legal information, matching precedents, and aiding judges in their decision-making.

6 Conclusion

The novel GNN-ERE framework is a key development in the design of legal knowledge graphs and intelligent case reasoning. By embracing graph neural networks and entity-relation extraction techniques, it provides a practical alternative to prior methods that extract shallow semantics from a study of text. The new approach allows for a fuller model of the complexity of legal rule structures, enabling cases that share contextual graph features and similarity of structural graph features to be accurately identified. The experimental evaluations demonstrated substantial gains across all evaluated metric domains, including entity extraction accuracy reaching 89.3%, relation precision reaching 96%, classification accuracy of 94%, and reasoning time of 298 ms. GNN-ERE demonstrated high scalability and strong interpretability, making the system flexible across multiple real-world applications. The GNN-ERE framework provides a robust solution for legal decision-making, being automated based on evidence that is timely, accurate, and explainable. This research lays the groundwork for the next generation of AI-based legal reasoning systems. The GNN-ERE framework enhances legal case analysis by effectively extracting entities and relations to create efficient knowledge graphs. More specifically, GNN-ERE achieves strong performance metrics; for instance, it obtains 89.3% entity extraction accuracy, 96% relation extraction precision, 94% classification accuracy, and a 98% F1 score for case similarity. In addition, GNN-ERE demonstrates efficiency by producing the graph in 9.8 ms and supporting reasoning in 298 ms, both results indicative of supporting real-time applications. In addition to efficiency, scalability is important - GNN-ERE constructs knowledge graphs from just over 1,000 documents without considerable performance degradation. Lastly, with respect to interpretability, GNN-ERE provides measures of its own interpretability, which is strong (≈89% - 92% in F1-score), illustrating GNN-ERE is a reliable, explainable, and scalable method for use in retrieval and decision-making support.

Future work is focused on enhancing the GNN-ERE framework to integrate multilingual legal texts, real-time adaptability, and judicial sentiment analysis to increase contextual understanding and abstraction. Moreover, strengthening the system's capacity for cross-jurisdictional legal reasoning and incorporating reinforcement learning techniques for adaptive case prediction is expected to expand the system's applicability across diverse and dynamic legal contexts.

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Improved Hybrid Model for Structural Vibration Control Using MOGA, LSTM, and Digital Twin Technology

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Keywords: Building structural vibration, long short-term memory, multi-strategy improved sparrow search algorithm, digital twin technology, genetic algorithm

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With the acceleration of urbanization, the vibration control of high-rise buildings is becoming increasingly prominent. To address the limitations of traditional methods on convergence and robustness against noise, this study proposes a hybrid intelligent control model that integrates a genetic algorithm with a long short-term memory neural network, while incorporating an improved sparrow search algorithm for parameter refinement and a digital twin framework for bidirectional data-driven control. Numerical experiments using seismic records from the PEER Ground Motion Database demonstrated that the proposed model achieved approximately 20% faster convergence compared with particle swarm optimization, whale optimization, and artificial fish swarm algorithms. The root mean square error of vibration prediction was reduced to 0.0180, the identified stiffness error of each floor remained below 1%, and the total control energy was reduced by about 15%. These results confirm the advantages of the proposed method on prediction accuracy, control efficiency, and stability, and highlight its potential applications in seismic design of high-rise structures and smart construction practices.

Povzetek: Opisan je hibridni inteligentni model za aktivno dušenje vibracij visokih stavb, ki združuje MOGA, LSTM, izboljšani algoritem iskanja z vrabci in digitalni dvojček. Rezultati kažejo bistveno boljšo natančnost napovedi, hitrejšo konvergenco in manjšo porabo kontrolne energije.

1 Introduction

Structural vibration control technology, as a cutting-edge field of science and technology, encompasses multiple disciplines, including civil disaster prevention, automatic control, and materials electronics [1]. Although traditional vibration control technology has solved theoretical complex system control problems, many difficulties still exist in practical engineering fields, such as significant differences between structural control system modeling and actual construction, and low sensor reliability in control algorithms [2]. Currently, with the development of science and technology, building structural vibration control technology has greatly improved, contributing to enhanced seismic resistance and comfort of structures. By adjusting structural vibration control strategies, engineers can find specific solutions to meet project requirements [3]. Structural vibration control strategies not only improve the dynamic performance of structures but also optimize parameter settings [4]. Existing methods include using Euler-Bernoulli beams for system dynamic analysis, building structural models based on the Newton-Euler method, and approximating system dynamics using the assumed mode method for wireless characteristics. These methods have greatly facilitated the design of subsequent controllers [5]. However, they also bring many challenges, such as incomplete controller designs and the inability of building walls to connect with vibration systems. Therefore, in response to difficulties in controlling vibrations of high-rise buildings and the unpredictability of sudden faults, this study constructs a hybrid model for intelligent control of building structural vibration, combining Multi-objective Optimization Genetic Algorithm (MOGA) and Long Short-Term Memory (LSTM) artificial neural network. During the model construction, the Multi-strategy Improved Sparrow Search Algorithm (MISSA) and Digital Twin technology are also utilized to predict and analyze the structural stability. It is expected that this model will greatly improve vibration control in high-rise buildings and have broader application prospects in the field of vibration control.

The innovation and contribution of this research lie in constructing a fusion model framework for intelligent control of building structural vibration based on the existing algorithms. For the first time, multi-objective genetic optimization, temporal depth prediction, global search enhancement, and digital twin technology are organically combined to form a closed-loop mechanism of "prediction - optimization - control". This model can not only improve the accuracy of vibration response prediction and real-time control strategy, but also achieve dynamic simulation of structural safety and fault adaptive capability through digital twin, providing a new approach for intelligent control in complex building scenarios.

2 Related work

In recent years, structural vibration control technologies have evolved from traditional passive devices to intelligent algorithm-driven methods. Passive control, as

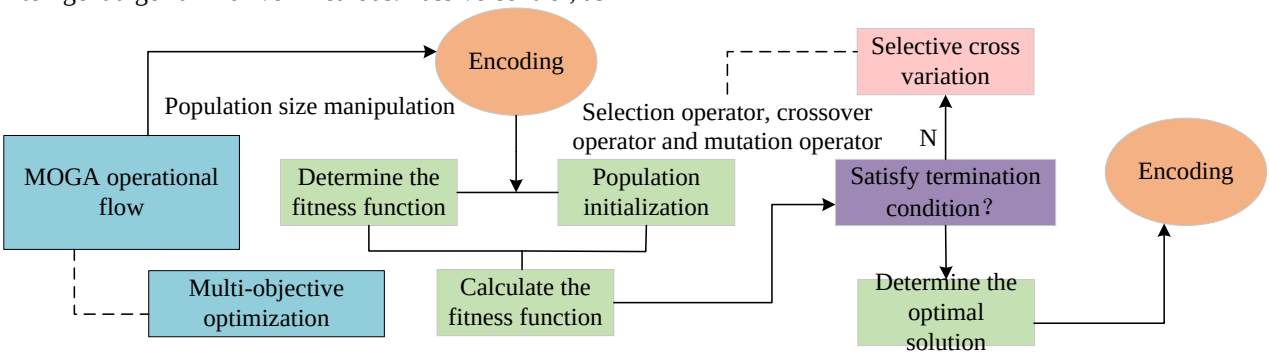


Figure 1: The specific process of the MOGA.

one of the earliest approaches, reduces structural responses by adding damping or mass adjustments. Chowdhury S et al. reviewed inertially amplified passive vibration control devices, demonstrating the potential applications of linear and nonlinear isolation systems in multi-degree-of-freedom structures [6]. Vázquez-Greciano A et al. and Yang F et al. summarized the development of tuned liquid dampers and tuned mass dampers, pointing out their advantages in reducing both horizontal and vertical vibrations, while also highlighting the challenges of optimal design and multi-frequency adaptability [7-8]. In addition, Patsialis D et al. proposed an optimization framework that coupled tuned mass dampers with inerter devices, emphasizing the importance of considering nonlinear behavior in multi-storey structures to improve vibration reduction performance [9].

In the field of semi-active control, magnetorheological dampers have gradually become a research hotspot. Cruze D et al. designed single- and multi-coil dampers and verified their energy dissipation performance under low power consumption, proving their applicability in seismic-resistant buildings and foundation isolation [10]. Bhowmik K et al. combined the LQG control strategy with the Bouc-Wen model to achieve semi-active vibration control of soft-storey buildings, significantly reducing inter-storey responses under various seismic excitations [11]. Kontoni D P N et al. further indicated that tuned mass dampers could effectively mitigate SSI effects in irregular steel high-rise buildings [12]. Zhang C W proposed the Active Rotary Inertia Driver (ARID) system, expanding the application scope of active control in bridges and large structures [13].

With the development of artificial intelligence and data-driven methods, AI-based vibration monitoring and control have gradually emerged. Zar A et al. reviewed the latest advances in vibration-based damage detection methods, pointing out the potential of deep learning in feature extraction and damage identification, while also revealing problems such as overfitting and data insufficiency [14]. AL Houri A et al. focused on the application of artificial intelligence in passive control structure design, emphasizing its advantages in optimizing isolation systems and enhancing disaster resilience [15].

In conclusion, extensive research has been conducted in structural vibration control by scholars worldwide, with notable achievements in vibration control. However, there is limited research on intelligent vibration control for building structures, particularly in areas such as state feature extraction and control goal recognition. Therefore, this study proposes a hybrid model for building structural vibration intelligent control, combining multi-objective optimization and LSTM. The hybrid model performs system parameter identification and control strategy calculation, making structural vibration control more effective and further enhancing the applicability of the control system.

3 Intelligent control of building structural vibration combining MOGA and LSTM

The study considers a multi-storey shear-type high-rise building, where each floor is treated as a single degree-of-freedom, with mass, stiffness, and damping characteristics taken into account. Under external loads such as earthquakes or wind excitations, the structure exhibits inter-storey displacements and accelerations. The control system obtains structural responses through sensors placed on key floors, while actuators apply the control forces. The main objective of this study is to significantly reduce inter story displacement and acceleration under limited maximum control force constraints, thereby ensuring the stability and safety of the structure under extreme load conditions.

3.1 Design of hybrid algorithm based on MOGA and LSTM

The construction industry has now entered the stage of intelligent development, and control algorithms are capable of precisely managing building structures [16]. However, with the continuous increase in the size and complexity of building structures, traditional control

algorithms tend to suffer from overfitting and have difficulty handling complex analyses [17]. To address these issues, this study proposes an intelligent control method that combines MOGA and LSTM, enabling intelligent optimization for complex building structures. The study proposes the following research questions and

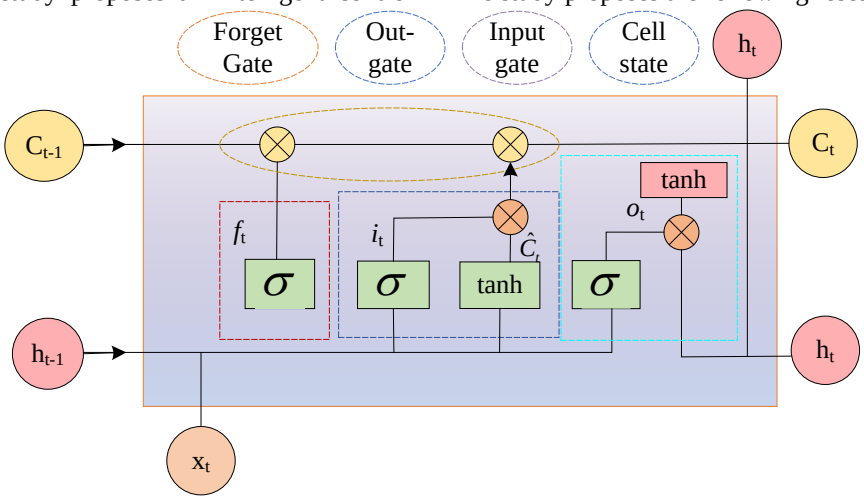


Figure 2: LSTM internal structure.

hypotheses: Can the integration of MOGA and LSTM improve the accuracy and convergence efficiency of structural vibration control? Can MISSA enhance global search ability and avoid local optima? Can digital twin technology improve the generalization and stiffness identification accuracy of the model in complex buildings? Accordingly, three hypotheses are formulated: H1: MOGA-LSTM achieves higher prediction accuracy than some existing optimization algorithms. H2: MISSA improves convergence speed and global optimization performance. H3: Digital twin technology can effectively enhance stiffness identification accuracy.

The specific process of the MOGA is shown in figure 1.

As shown in figure 1, the principle of MOGA is composed of encoding and population initialization, fitness evaluation, selection, crossover, and mutation operations, as shown in figure 1. The crossover and mutation operations in MOGA help with spatial exploration and prevent premature convergence, maintaining population diversity. MOGA can perform single-objective optimization. The fitness function model is denoted in equation (1).

$$\min_{X} J(X) = \alpha PIDR_{\max}(X) + \beta RMS_{acc}(X) + \gamma E_{ctrl}(X) \quad (1)$$

In equation (1), X represents the parameter to be optimized encoded by MOGA. $PIDR_{\max}$ is the peak inter-story displacement ratio, which is used to measure the maximum inter-story deformation of the structure under earthquake action. RMS_{acc} is the root mean square of the floor acceleration, which reflects the comfort and safety of the structural vibration. E_{ctrl} is the control energy, which is obtained by integrating the square of the actuator control force over the entire time history and reflects the control cost. α, β, and γ respectively represent weight coefficients, which are used to balance the importance of the three factors, thereby comprehensively optimizing structural safety, comfort, and economy. The multi-objective optimization setting of MOGA is shown in equation (2).

$$\begin{cases} d_i = \sum_{j=1}^{n} d_i^j \\ I = \{i_1, i_2 \cdots, i_m\} \\ d_{ik}^j = f_j(i_{k+1}) - f_j(i_{k-1}) \end{cases} \quad (2)$$

In equation (2), I represents the individual sequence. i_k denotes the individual. d_i represents the total sum of individual crowding distances. MOGA integrates multiple objective functions, as shown in equation (3).

$$F(x) = \sum_{i=1}^{n} w_i f_i(x) \quad (3)$$

In equation (3), $F(x)$ represents the objective function, and w is the weight vector, with $w_i \geq 0$. MOGA optimizes building load objectives and improves the energy-efficient design of building structures. LSTM captures long-distance data from information and adjusts parameters. Therefore, the study combines the improved GA with LSTM. The internal structure of LSTM is presented in figure 2.

As shown in figure 2, the LSTM mainly consists of the input gate, forget gate, output gate, and cell state. The cell state selectively allows information to pass through or be forgotten, maintaining stability during processing. The forget gate determines which information to discard from the cell state, the input gate updates the cell state, and the output gate decides the output information. Thus, the LSTM can determine the direction of the time series. The updated input gate of LSTM is shown in equation (4).

$$\begin{cases} i_t = \sigma(W_t \times [x_t, h_{t-1}] + b_i) \\ \hat{C}_t = \tanh(W_c \times [x_t, h_{t-1}] + b_i) \end{cases} \quad (4)$$

In equation (4), W_t and W_c represent the weights. b_i and i_t represent the biases, which decide whether the

input gate data can enter the t state. The greatest advantage of LSTM is its memory capability, as it connects both the previous and the subsequent time steps, continuously updating information in the predictive

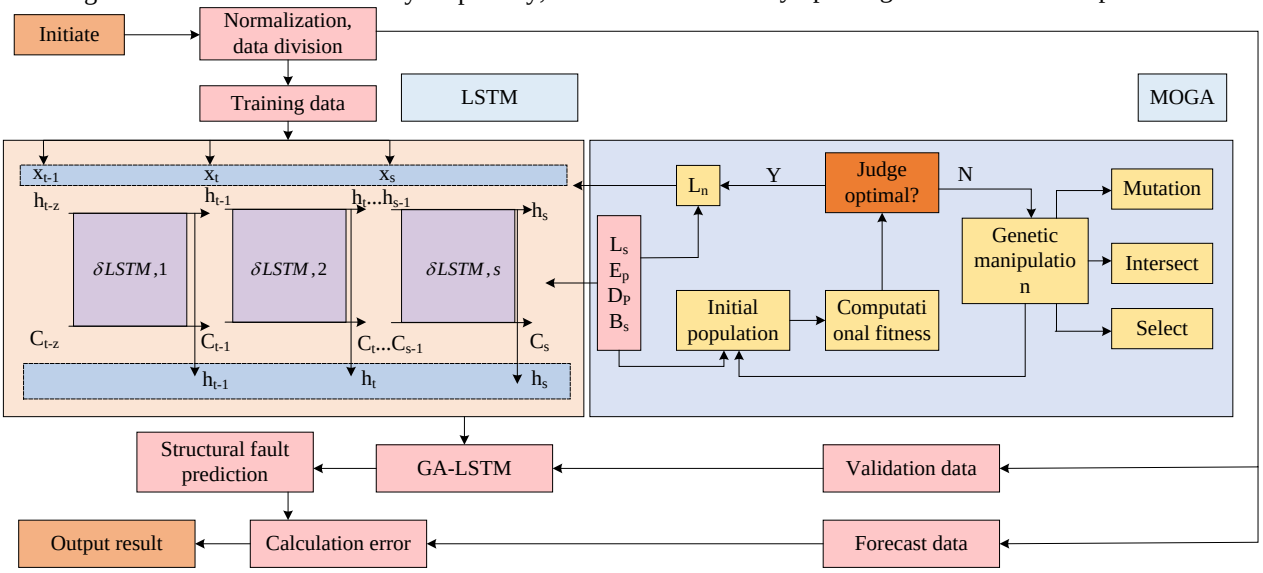


Figure 3: MOGA-LSTM control optimization algorithm flow.

monitoring memory block. Therefore, to address the challenges posed by the complex and variable data of building structures, as well as the potential failures of the building control system, this study combines the global search capability of MOGA and the effective sequence data processing ability of LSTM. This study proposes an MOGA-LSTM-based control optimization algorithm to improve the building structure. The algorithm flowchart is presented in figure 3.

As shown in figure 3, MOGA-LSTM is mainly divided into the input layer, LSTM layer, GA layer, and output layer. First, the data is normalized and divided. Then, the training data is processed, and the hidden data features are extracted through multiple layers of LSTM. Next, the characteristics of MOGA are used to determine the actual parameters of the LSTM layer. Finally, the data from the transmission process is weighted and summed in the output layer, and the error in the structure is calculated. The final output is shown in equation (5).

$$\begin{cases} r_t = \sigma\left(W_r \times \left[x_t, h_{t-1}\right] + b_r\right) \\ h_t = r_t \times \tanh\left(C_t\right) \end{cases} \tag{5}$$

In equation (5), W_r represents the final output weights. b_r represents the final bias of the input gate. h_t represents the final output of the hidden layer. When the forget gate filters the information, the calculation is shown in equation (6).

$$\begin{cases} I_t = \sigma\left(W_I \times \left[x_t, h_{t-1}\right] + b_I\right) \\ C_t = i_t \times \hat{C}_t + I_t \times C_{t-1} \end{cases} \tag{6}$$

In equation (6), at time t, the input to the neuron is x_t. h_t represents the output of the neuron. σ is the activation function of the neuron. I_t is the final result of the forget gate. Therefore, MOGA is primarily employed to perform global optimization of key hyperparameters in LSTM. Its search space covers network structure, learning rate, and batch size, with individuals represented using real-number encoding. The fitness function jointly considers prediction error, inter-story drift suppression, and control energy to achieve multi-objective optimization. Meanwhile, constraints are imposed to ensure that the results satisfy actuator saturation and structural stability requirements, thereby guaranteeing their physical rationality and engineering feasibility.

3.2 Design of hybrid model for building structural vibration intelligent control based on MISSA and digital twin

The vibration stability of building structures plays a decisive role in the quality of buildings. Unavoidable natural disasters pose significant challenges to the design of building structures [19]. Currently, in the field of building structure control, there are issues in control algorithms and actuator development, such as large modeling errors compared to the actual structure and low reliability of control systems [20]. While MOGA-LSTM offers some assistance in optimizing structural data, there are still shortcomings in structural vibration stability. Therefore, to address issues such as the time delay in building structure control forces and prioritization of measurement points, this study improves MOGA-LSTM by incorporating a multi-strategy enhanced sparrow search algorithm for building structural vibration intelligent control. MISSA is mainly embedded as a global optimizer within the MOGA-LSTM model to further refine candidate solutions through local fine-tuning. The optimization parameters mainly focus on the learning rate of LSTM and the distribution of hidden neurons, aiming to improve the convergence speed and stability of the model under complex seismic excitations. MISSA is activated after MOGA converges to a near-optimal solution, and it enhances population diversity through chaotic initialization, sine-cosine updates, and Lévy flight

strategies, thereby avoiding local optima and achieving superior hyperparameter configurations in the

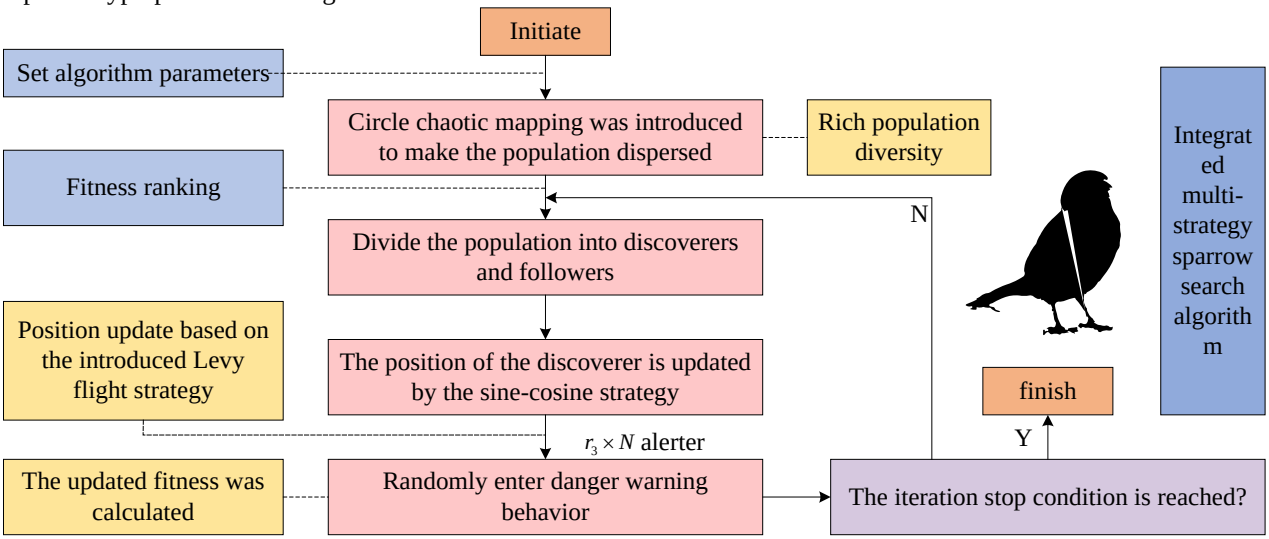


Figure 4: Specific flow of MISSA.

later iterations. The improved Circle chaotic mapping initialization of the population is shown in equation (7).

$$X_{k+1} = \mathrm{mod}\left[d_1 x_k + d_2 - \frac{d_3}{d_1 \pi} \sin\left(d_1 \pi X_k\right), 1 \right] \tag{7}$$

In equation (7), k represents the dimension of the solution. d_1, d_2, and d_3 represent the parameters. The position of the MISSA discoverer is improved by incorporating the cosine-sine algorithm. The update calculation is shown in equation (8).

$$\begin{cases} \omega = \omega_{\min} + \left(\omega_{\max} - \omega_{\min}\right) \cdot \sin\left(t\pi / T_{\max}\right) \\ X_{n,m}^{t+1} = \begin{cases} \left(1-\omega\right) \cdot X_{n,m}^{t} + \omega \cdot \sin\left(r_1\right) \cdot \left| r_2 \cdot X_{best} - X_{n,m}^{t} \right|, R_2 < ST \\ \left(1-\omega\right) \cdot X_{n,m}^{t} + \omega \cdot \cos\left(r_1\right) \cdot \left| r_2 \cdot X_{best} - X_{n,m}^{t} \right|, R_2 \geq ST \end{cases} \end{cases} \tag{8}$$

In equation (8), t represents the number of iterations. ω is the nonlinear decreasing factor, $X_{n,m}^{t}$ is the position of the n-th sparrow at the t-th iteration in the m-th dimension, and r_1 represents the random number on $0 \sim 2\pi$. MISSA adopts the Lévy flight strategy to improve optimization accuracy. The position update for the joiner is shown in equation (9).

$$\begin{cases} Levy\left(x\right) = \dfrac{0.01u}{\left|v\right|^{\frac{1}{\xi}}} \\ x_{n,m}^{t+1} = x_{best}^{t} + \left(x_{best}^{t} - x_{worst}^{t}\right) \cdot \lambda \cdot Levy\left(d\right) \end{cases} \tag{9}$$

In equation (9), ξ ranges within $\left[1,3\right]$. λ is a random number between $0 \sim 1$. d represents the problem dimension to be solved. The position update for the sentinel in MISSA is shown in equation (10).

$$X_{n,m}^{t+1} = \begin{cases} X_{best}^{t} + \beta \cdot \left| X_{n,m}^{t} - X_{best}^{t} \right|, if, f_n > f_g \\ X_{n,m}^{t} + K \cdot \left(\dfrac{\left| X_{n,m}^{t} - X_{worst}^{t} \right|}{\left(f_n - f_w\right) + \varepsilon} \right), if, f_n = f_g \end{cases} \tag{10}$$

In equation (10), X_{best}^{t} represents the best position, β is a normally distributed random number, and 1 is the variance value. f_n represents the fitness value of the n-th individual, where f_g represents the best fitness and f_w represents the worst fitness. In summary, MISSA can perform global optimization on complex structural data and avoid the local optima. The specific process of MISSA is shown in figure 4.

In figure 4, the sparrow algorithm improved with multiple strategies initializes the population by using circle chaotic mapping. After initializing the population, the positions of discoverers and joiners are updated using the cosine strategy and Lévy flight strategy. Once the positions are updated, the fitness of the updated positions is calculated. The algorithm then checks whether the individual positions exceed the boundaries of the search space and whether the iteration count satisfies the conditions. As building structural vibrations have poor adaptability to external environments due to time delays during actual control, this study combines the MISSA global search with digital twin technology to perform safety analysis and prediction on the building structural framework, enhancing the intelligent control of building structures. Digital twin technology enables dynamic collaboration of structures and supports virtual physical interaction configuration modeling to achieve structural security and intelligent control. The safety intelligent framework of the digital twin building structure is shown in equation (11).

$$F_{DT} = \left(S_{\mathrm{Pr}}, S_{vm}, P_{td}, L_{fa}, C_n\right) \tag{11}$$

In equation (11), S_{Pr} and S_{vm} represent the physical structure entity and the virtual structure model. P_{td} and L_{fa} represent the twin data processing layer and the functional application layer. C_n represents the connections between the structural components. The

specific structural safety intelligent control framework of digital twin technology is shown in figure 5.

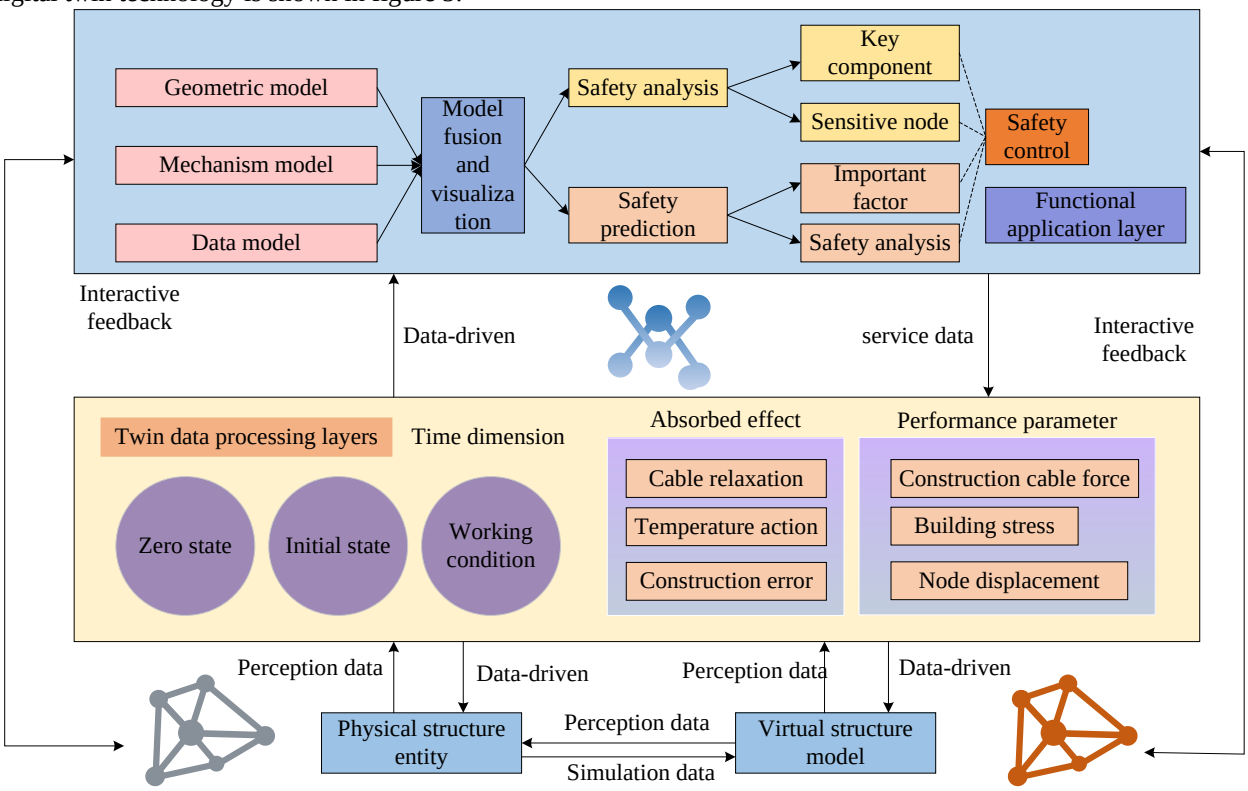


Figure 5: Intelligent control framework for structural safety.

In figure 5, the structure security intelligent framework based on digital twin mainly consists of functional application layer, twin data processing layer, and virtual and physical structure simulation modules. The twin data processing layer incorporates both temporal and spatial dimensions. In the temporal dimension, vibration response data are collected in real-time by sensors and transmitted to the twin, where the virtual model dynamically updates its state based on the physical data and then feeds the corrected prediction back to the physical structure, thereby achieving bidirectional synchronization between the virtual and physical systems. In the spatial dimension, the twin model simultaneously analyzes load-bearing parameters and performance parameters to assess the overall structural safety. With regard to the data processing pipeline, the twin sequentially executes data acquisition, cleaning, feature extraction, prediction, and comparison with subsequent correction. To address sensor noise and model uncertainty, error correction methods and confidence interval constraints are applied, which improves stability and reliability. Furthermore, real-time constraints such as upper limits on sampling frequency and feedback delay have been introduced to ensure that prediction and control commands can be applied to physical structures within acceptable engineering time windows.

The digital twin assumes different roles at different stages. During the training stage, it generates or augments diverse datasets based on the virtual model to enhance the generalization capability of the MOGA-LSTM. During the inference stage, the outputs of the MOGA-LSTM are compared with the simulation results of the virtual model. The global optimization ability of MISSA is employed to refine parameters and update strategies. Through this approach, digital twin can not only intelligently analyze building structures, but also reduce modeling errors in design and construction processes, thereby improving safety prediction and control performance under complex environmental conditions. The specific expression of its safety control is given in equation (12).

$$f\left(\varphi_1,\varphi_2,\cdots,\varphi_m\right)\xrightarrow{R}g\left(\mu_1,\mu_2,\cdots,\mu_m\right) \tag{12}$$

In equation (12), $f\left(\varphi_1,\varphi_2,\cdots,\varphi_m\right)$ represents the set of mechanical parameters. R denotes the limits within the parameter specifications. $g\left(\mu_1,\mu_2,\cdots,\mu_m\right)$ represents the set of intelligent control measures. Therefore, to address issues such as the time-varying nature of building material properties and unstable safety performance, this study combines MOGA-LSTM with global optimization and digital twin technology of MISSA for prediction and simulation. A hybrid model based on MISSA and digital twin is developed for intelligent vibration control of building structures. The mechanism of this model integration is shown in figure 6.

From figure 6, digital twin technology enables simulation and measurement output, while the combination of MISSA and MOGA-LSTM allows for safety prediction and key parameter setting of the structure. The data is then analyzed and predicted intelligently, and transmitted to the multidimensional

physical system for precise execution. Driven by digital twin and MISSA algorithms, a hybrid model of

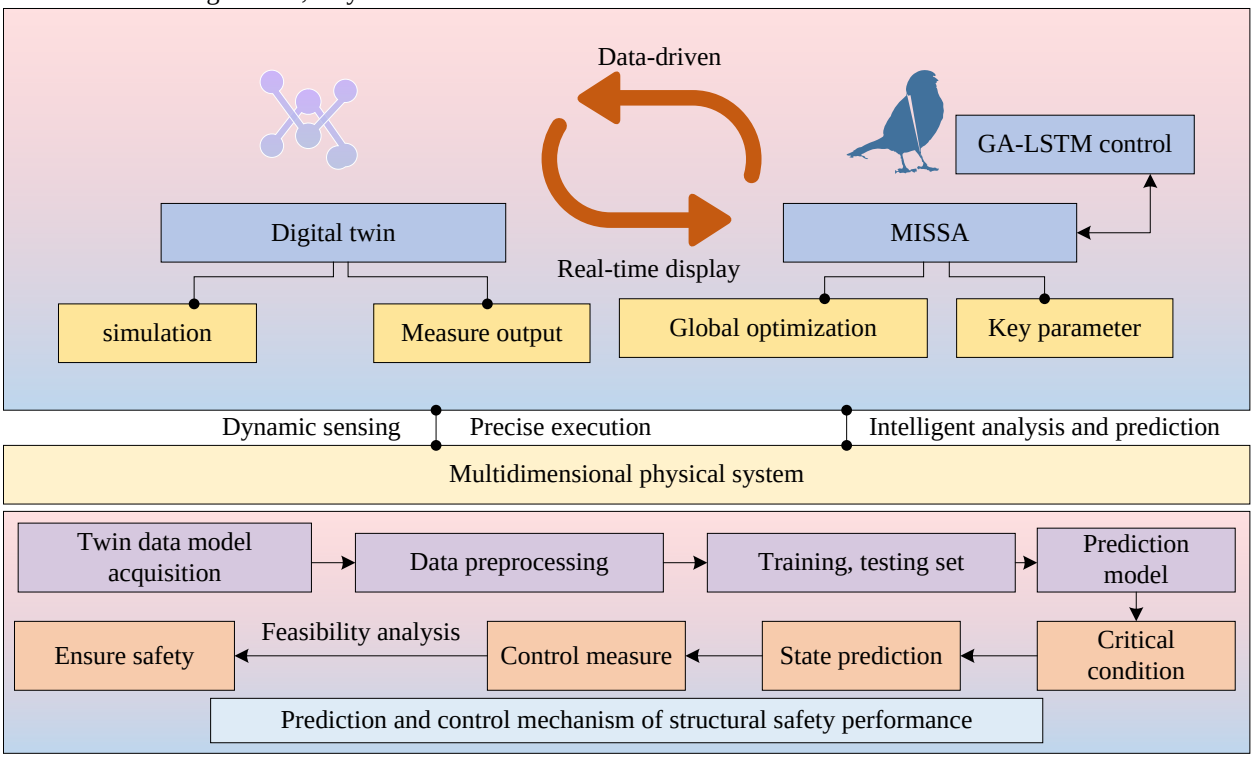


Figure 6: Structure intelligent control hybrid model framework.

intelligent vibration control for building structures based on MISSA and digital twin can detect and capture unsafe factors in the structure, thereby controlling the key factors of building structural vibration.

4 Performance verification of the improved hybrid model for intelligent vibration control of building structures

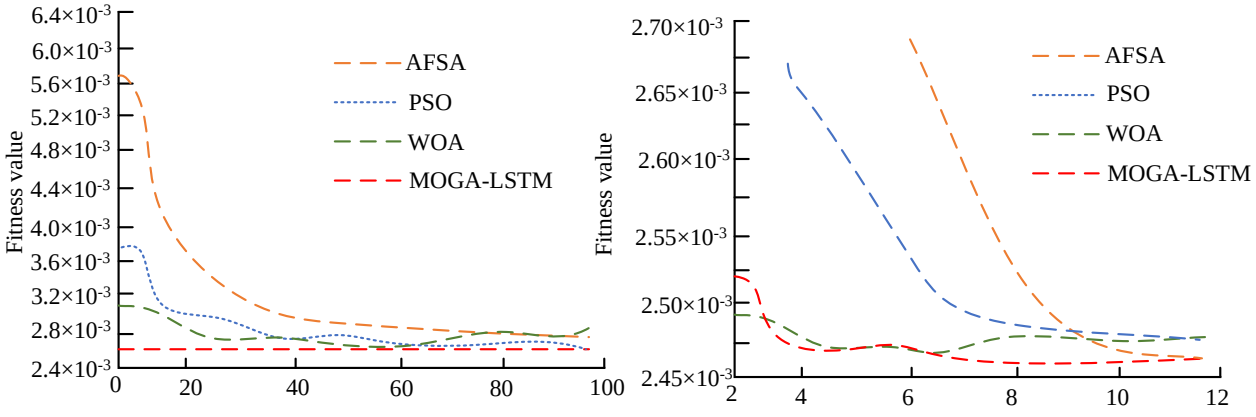
4.1 Comparison and analysis of MOGA-LSTM performance

To highlight the superior performance of MOGA-LSTM, the study compared it with Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), and Artificial Fish Swarm Algorithm (AFSA). In terms of the experimental environment, Matlab R2019b is used as the primary software, supplemented by Python 3.9. The deep learning framework is PyTorch 1.12.1, with GPU acceleration enabled by CUDA 11.6. Numerical computation and data processing rely on NumPy 1.21 and SciPy 1.7, while visualization is carried out using Matplotlib 3.5 and Seaborn 0.11. The hardware configuration includes an Intel i7-12650H @ 2.30GHz CPU, an NVIDIA RTX 3070 GPU, and 32 GB of memory, running on the Windows 11 operating system. In terms of algorithm parameter settings, to ensure fairness, the maximum number of iterations for all optimization algorithms is set to 100, and the fitness function evaluation criteria are kept consistent. For PSO, the population size is 50, the inertia weight is 0.7, and both learning factors c1 and c2 are set to 1.5. For WOA, the population size is 50, and the encircling parameter decreases linearly. For AFSA, the fish school size is 50, the visual range is 5, the step length is 0.5, and the crowding factor threshold is 0.75. In the MOGA-LSTM, the genetic algorithm takes a population size of 100, a crossover probability of 0.8, and a mutation probability of 0.1. The maximum number of iterations is also set to 100. The LSTM network consists of two hidden layers with 128 neurons each, a learning rate of 0.001, and a batch size of 64. All methods are run with the same data split and random seed to ensure fairness and reproducibility of the experimental results.

The study employs two public datasets, namely the PEER Ground Motion Database and the IASC-ASCE SHM Benchmark Dataset. The former contains typical seismic acceleration time-history records, which are used to verify the model's vibration prediction and control performance under earthquake loads. The latter provides frame structural vibration response data from a structural health monitoring benchmark, which are used to train and test the model's parameter identification and control performance. To validate the convergence performance of the MOGA-LSTM hybrid algorithm in building structures, the four control algorithms, including PSO, WOA, AFSA, and MOGA-LSTM, are tested using the Schaffer benchmark function, and the test results are shown in figure 7.

As shown in figure 7(a), AFSA achieved complete convergence under the Schaffer benchmark function after 40 iterations, while PSO and WOA converged between the 20th and 40th iterations. In contrast, MOGA-LSTM

remained relatively stable throughout the entire 100 iterations. From figure 7(b), it was evident that MOGA-



(a) Complete convergence under Schaffer function

(b) Initial iteration convergence effect

Figure 7: Algorithm convergence under Schaffer benchmark function.

Table 1: Results of ablation experiment.

Configuration	Convergence Iterations	Best Validation RMSE	RMSE Std
(i) LSTM only	100 ± 0	0.0320	0.0040
(ii) LSTM + MOGA	95 ± 3	0.0241	0.0021
(iii) LSTM + MISSA	92 ± 4	0.0232	0.0025
(iv) LSTM + MOGA + MISSA	78 ± 5	0.0190	0.0014
(v) LSTM + MOGA + MISSA + Digital twin	68 ± 4	0.0180	0.0012

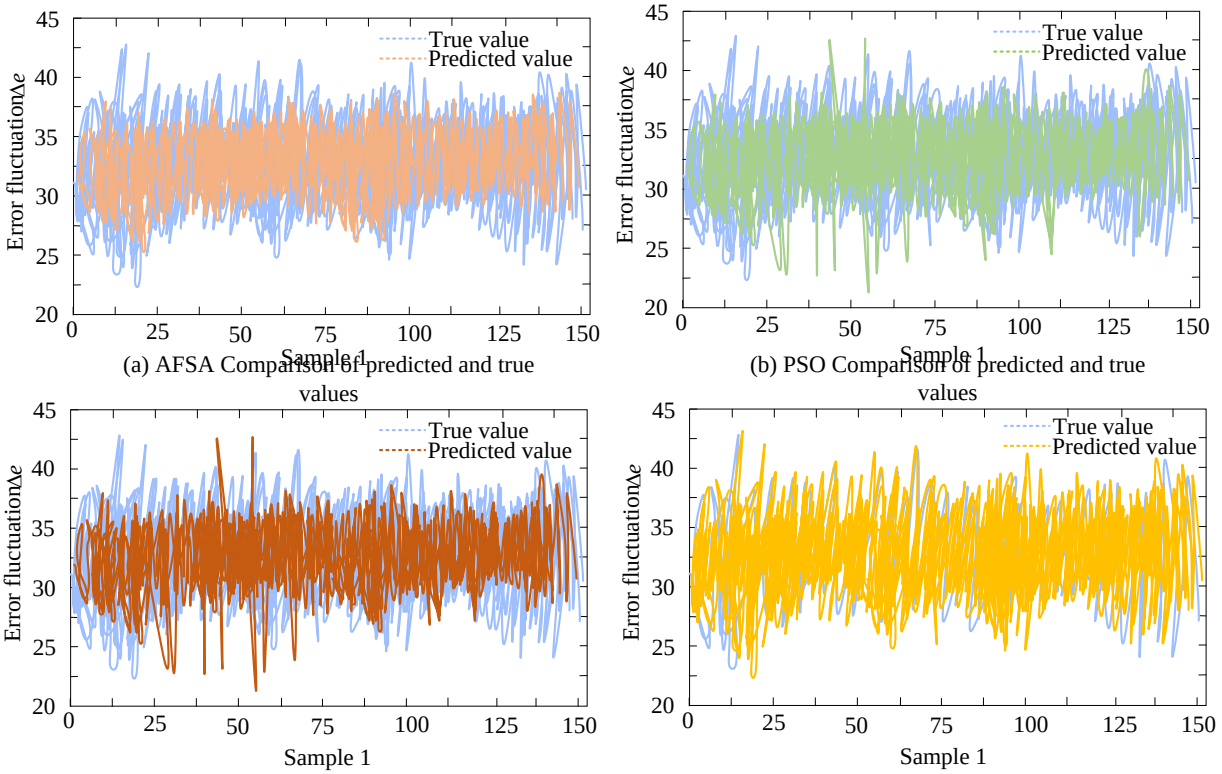
LSTM converged after 6 iterations, while PSO, WOA, and AFSA all showed less effective convergence. Therefore, MOGA-LSTM demonstrated lower training errors and better convergence performance. Further ablation experiments are conducted, and the results are shown in Table 1.

From Table 1, with the progressive introduction of GA, MISSA, and the digital twin module, the model exhibited clear improvements in convergence speed, prediction accuracy, and stability. When GA or MISSA was added, the number of iterations decreased and the validation error was reduced, indicating that both global search and local refinement enhanced model performance. When GA and MISSA were combined, the convergence was significantly accelerated, errors were further reduced, and the results became more stable. After adding the digital twin, the model achieved the best performance on convergence efficiency and prediction accuracy, while also maintaining high consistency across multiple runs. In summary, the complete framework performed best across all metrics, confirming the necessity and effectiveness of incorporating each module.

To better illustrate the prediction performance of MOGA-LSTM in building structural control, this study takes floor acceleration response as the primary prediction variable. The data is sourced from the PEER Ground Motion Database (such as the El Centro seismic records), which drives the vibration response of the IASC-ASCE benchmark frame structure. All seismic records are sampled at a rate of 0.01 s, with a total duration of 60 s. The data is divided into 70% for training, 15% for validation, and 15% for testing, and zero mean Gaussian noise and 0.005g standard deviation are added to the test set to simulate sensor measurement errors. The predicted values and true values of PSO, WOA, AFSA, and MOGA-LSTM are compared, and the results are shown in Figure 8.

As shown in figure 8(a), the predicted values of AFSA for sample 1 mainly concentrated in the central region, with error fluctuations predominantly in the range of 40-45. In figure 8(b), PSO exhibited larger error fluctuations for sample data between 15 and 50, and the error was more evident when compared to the real values. In figure 8(c), WOA showed significant error fluctuations between sample data 25 and 75, with clear up-and-down variations. However, as shown in figure 8(d), MOGA-LSTM's predicted values aligned closely with the real values, with a prediction accuracy of 97.56%. Therefore, MOGA-LSTM achieved higher prediction accuracy, smaller error fluctuations, and better data control analysis. To further highlight the prediction performance in building structures, the study also compared the mean squared error and prediction error for PSO, WOA, AFSA, and MOGA-LSTM. In addition to these four algorithms, Multiple Objective Particle Swarm Optimization (MOPSO) and Spider Wasp Optimizer (SWO) are added to increase the diversity of the comparison results. The comparison results are shown in Table 2.

As shown in Table 2, PSO had the longest running time at 51s, with the maximum relative error reaching 61.24%. MOGA-LSTM had the shortest running time at 13s, with a root mean square error of 1.248 and a maximum relative error of 15.142%. MOPSO had the



(a) AFSA Comparison of predicted and true values

(b) PSO Comparison of predicted and true values

(c)WOA Comparison of predicted and true values

(d) MOGA-LSTM Mixing Comparison of predicted and true values

Figure 8: Predicted state comparison chart.

Table 2: Comparison of mean square error and prediction error results.

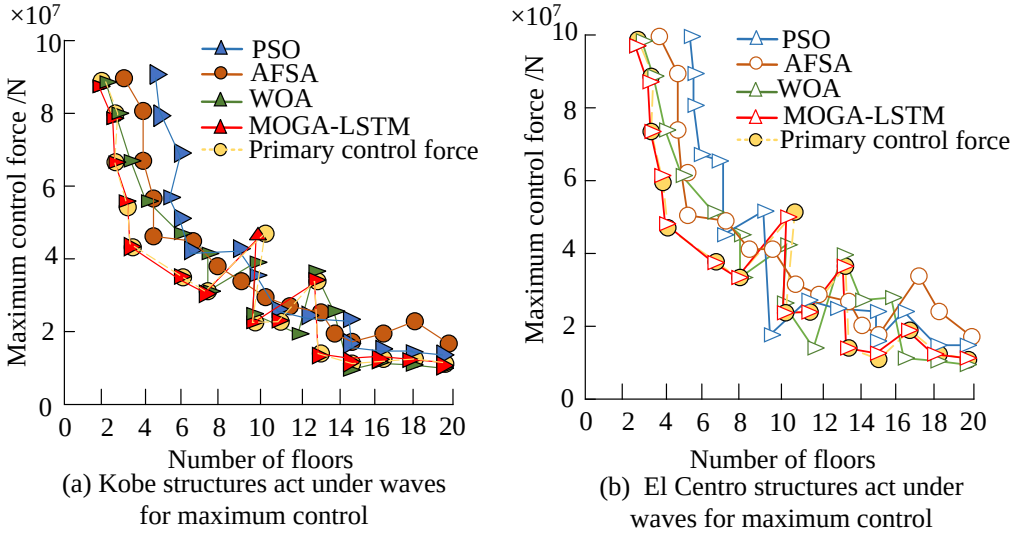
Algorithm	Running time/s	Root mean square error	Maximum relative error/%	Mean absolute error/%	Mean relative error/%
PSO	51	5.014	61.245	5.210	11.487
WOA	43	4.348	48.361	4.168	7.468
AFSA	60	4.126	34.786	4.032	6.875
MOGA-LSTM	13	1.248	15.142	1.478	4.210
MOPSO	25	3.216	26.132	2.676	5.168
SWO	36	2.487	30.456	2.148	5.014

second longest running time at 25s, with a mean relative error of 5.168%. The mean relative error of SWO was very close to MOPSO, with a difference of only 0.514%. The MOGA-LSTM hybrid algorithm demonstrated higher operational efficiency in building structure control, better handling data errors, and strengthening structure failure prediction.

4.2 Performance analysis of the hybrid model for intelligent vibration control of building structures with integrated algorithms

To further verify the superior performance of the building structural vibration intelligent control model based on MOGA-LSTM, it is compared with the building structural vibration intelligent control models constructed using PSO, WOA, and AFSA algorithms. Since the building structural vibration control system is susceptible to natural factors, which can lead to structural safety instability, the study tests the generalization performance of the MOGA-LSTM-based building structural vibration intelligent control model. In the simulation, the control force is generated by active mass dampers installed at the top and critical floors of the structure. To ensure engineering feasibility, the maximum control force is set to 1×108 N, while considering force and velocity saturation constraints. All stiffness parameters are expressed in N/m, and control forces are expressed in N to maintain consistency in physical units. The uncontrolled structural response is selected as the baseline for evaluating the relative improvement achieved by the proposed control strategy. The results for models constructed using MOGA-LSTM, PSO, WOA, and AFSA are shown in figure 9.

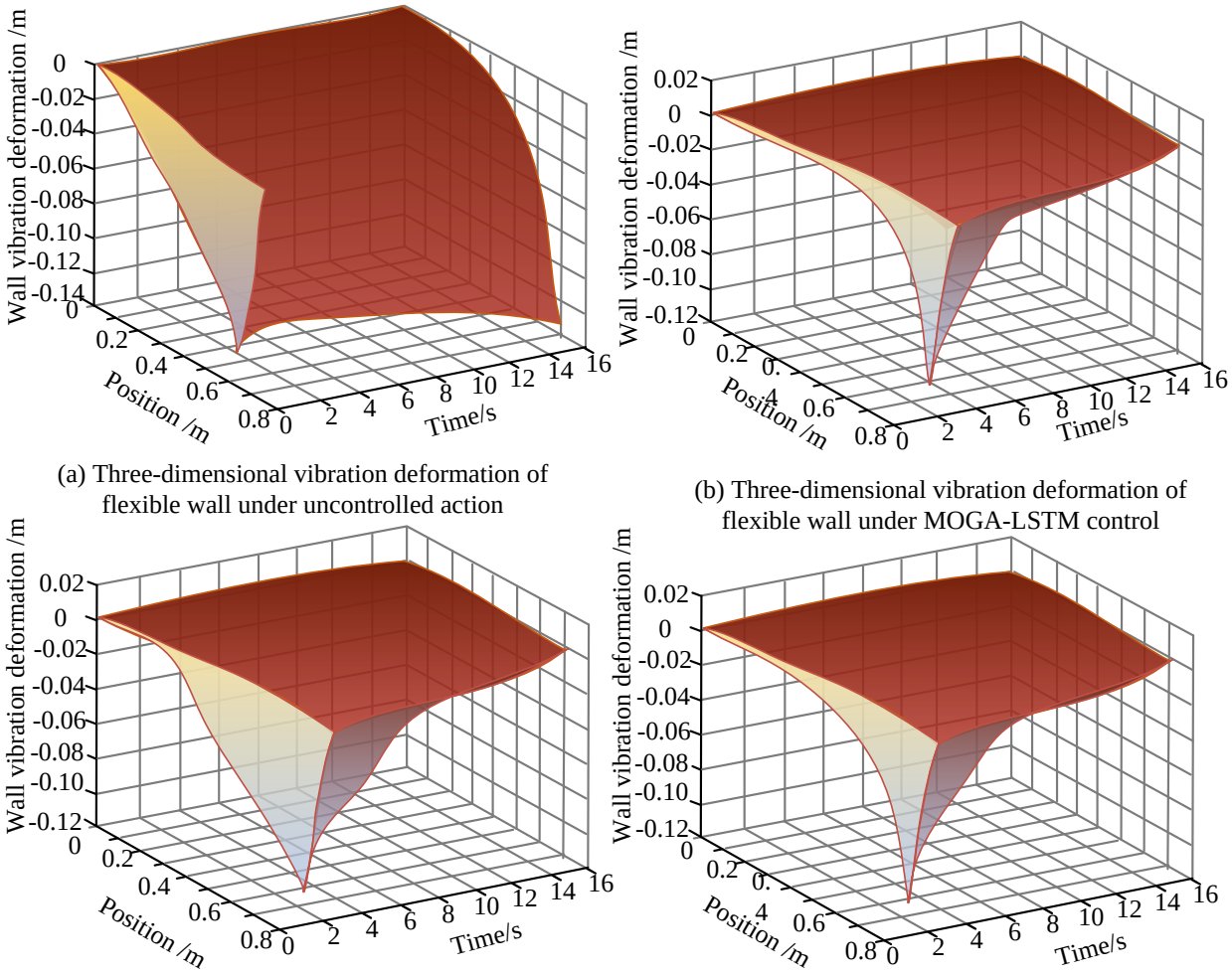
From figure 9(a), influenced by the Kobe wave, the control force of the MOGA-LSTM model was close to the original applied force. The WOA model showed a maximum control force of 2×107 N at the 11th floor. From figure 9(b), the AFSA model showed a maximum control force of 3×107 N at the 16th floor, with a significant error compared to the original maximum control force calculation. In conclusion, the MOGA-LSTM model exhibited better generalization



(a) Kobe structures act under waves for maximum control

(b) El Centro structures act under waves for maximum control

Figure 9: Generalized performance test.



(a) Three-dimensional vibration deformation of flexible wall under uncontrolled action

(b) Three-dimensional vibration deformation of flexible wall under MOGA-LSTM control

(c) Three-dimensional vibration deformation of flexible wall under PSO control

(d) Three-dimensional vibration deformation of flexible wall under WOA control

Figure 10: Comparison of 3D vibration deformation curve of flexible wall.

performance and stronger control adaptability. To further verify the control performance of the MOGA-LSTM model, it is compared with the PSO and WOA models through a three-dimensional simulation experiment of a flexible wall. The simulation results are shown in figure 10.

Table 3: Stiffness identification of each floor.

Floor	1	2	3	4	5	6	7	8	9	10
True stiffness	3.28	8.64	8.64	8.64	7.12	5.68	5.68	5.67	5.67	5.67
Identified stiffness	3.271	8.634	8.650	8.634	7.116	5.674	5.671	5.664	5.664	5.650
Floor	11	12	13	14	15	16	17	18	19	20
True stiffness	5.00	5.00	5.00	3.94	2.97	2.97	2.97	2.97	2.35	1.90
Identified stiffness	4.981	5.041	5.004	3.954	2.961	2.964	2.965	2.981	2.341	1.910

Table 4: Comparison of control performance for different methods on a 20-floor building.

Method	Peak PIDR (%)	RMS Acceleration (m/s2)	Control Energy (N·m)	Stabilization Time (s)
Uncontrolled	2.85	0.412	/	12.4
TMD	2.10	0.326	/	10.6
LQR	1.75	0.298	1.24×106	8.7
MOGA-LSTM	1.42	0.251	9.85×105	5.3

In the 3D simulation of the flexible wall shown in Figure 10, the wall height, width, and thickness were set according to typical frame structure parameters, with the base fixed and the top free. The model was discretized using a finite element mesh, and damping characteristics were represented by a Rayleigh model that considered both material and structural damping. Control forces were subject to saturation and rate limits, sensors were placed at the top and mid-height of the wall to monitor displacement and acceleration, and the Newmark-β method was used to ensure numerical stability. From figure 10(a), under the initial condition, the vibration deformation of the single-floor building without control could not converge to 0. From figure 10(b), the MOGA-LSTM model stabilized the wall vibration at 5 s. Figure 10(c) showed that the PSO model stabilized the wall vibration at 8 s. Figure 10(d) indicated that the WOA-based building structural vibration control model still showed wall deformation between 4 and 6 s. Therefore, the MOGA-LSTM model effectively suppressed the vibration deformation of the flexible wall and exhibited better convergence. To further validate the parameter identification performance of the MOGA-LSTM model, stiffness identification was conducted for a 20-floor building under the El Centro ground motion. The input ground motion was obtained from the PEER Ground Motion Database, with a sampling rate of 0.01 s and a total duration of 60 s. Gaussian noise with zero mean and a standard deviation of 0.005 g was added to the test data to simulate sensor measurement errors. Stiffness identification was performed using a prediction error minimization-based MOGA-LSTM approach, in which the prediction errors of floor acceleration and displacement were used as the loss function to optimize the LSTM hyperparameters and output the estimated stiffness of each floor, while regularization constraints were incorporated to enhance stability. Each reported result represents the average of 20 independent trials, and relative errors are provided. The identification results are summarized in Table 3.

As shown in Table 3, the identified stiffness error of the MOGA-LSTM model was below 1% for all floors. Specifically, the identified stiffness on the 19th floor was 2.341, while the actual value was 2.35, with a relative error of 0.37%. For the 12th floor, the identified value was 5.041, differing from the true value of 5.00 by 0.82%. These results demonstrate that the proposed hybrid model maintains high stability and accuracy under noisy conditions, effectively identifying the stiffness parameters of high-rise building structures and showing good applicability and robustness in structural vibration control.

To further verify the vibration control performance of the MOGA-LSTM model, comparative experiments are conducted on a 20-floor building under the El Centro and Kobe ground motions. The seismic records were obtained from the PEER Ground Motion Database, with a sampling rate of 0.01 s and a total duration of 60 s. During the simulation process, the saturation and rate limits of the actuator were uniformly applied. The comparison involves a Linear Quadratic Regulator (LQR), a Tuned Mass Damper (TMD), and the proposed MOGA-LSTM model, with the uncontrolled case set as the baseline. The evaluation metrics include Peak Inter-floor Drift Ratio (PIDR), Root Mean Square (RMS) floor acceleration, and total control energy. Each result is averaged over 20 independent trials, and relative errors are reported. The results are summarized in Table 4.

As shown in Table 4, the MOGA-LSTM model outperformed traditional methods across all evaluation metrics. Compared with the uncontrolled case, the peak PIDR was reduced by approximately 50% and the RMS floor acceleration by about 39%. Compared with TMD and LQR, MOGA-LSTM demonstrated a much shorter stabilization time, requiring only 5.3 s to reach steady state. These results indicate that the proposed hybrid model not only achieves significantly better vibration mitigation than classical control methods, but also exhibits stronger engineering applicability on energy efficiency and response stability.

5 Conclusion

To address the long calculation time for control signals and high hardware costs in building structures, this study developed an MOGA-LSTM-based hybrid intelligent control model for structural vibration suppression. The model integrated MISSA and digital twin technology to detect and capture structural safety risks. To evaluate the performance of the hybrid control model, it was compared with PSO, WOA, and AFSA from convergence effects and other aspects. Experimental results showed that the MOGA-LSTM model converged after 6 iterations with a

prediction accuracy of 97.56%. In contrast, the prediction accuracy of PSO, WOA, and AFSA was 92.15%, 94.56%, and 95.12%, respectively, all of which were lower than that of MOGA-LSTM. Furthermore, the MOGA-LSTM-based control model achieved the best control effect on flexible wall structures at 5 s, gradually stabilizing thereafter. In comparison, the PSO- and WOA-based models achieved optimal control at 6 s and 8 s, respectively, which were not as effective as the MOGA-LSTM model.

Overall, the proposed MOGA-LSTM model not only demonstrates favorable convergence and stability in experiments, but also provides a scalable intelligent solution for structural vibration control in buildings. From a state-of-the-art perspective, the model can be deeply integrated with digital twin, IoT-based sensor networks, and intelligent monitoring platforms, thereby laying the foundation for dynamic safety assessment and predictive maintenance throughout the building lifecycle. In practical applications, the approach can be extended to seismic design of high-rise buildings, structural monitoring of bridges and tunnels during construction, risk warning in construction processes, and real-time control and feedback in smart construction environments, highlighting its broad application prospects and practical value in the building technology and construction domains. Although this study did not explore the vibration suppression and intelligent adjustment of multi-floor flexible high-rise building systems, further research in this area is recommended in the future.

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