Analysis of Customer Comment Data on E-commerce Platforms Based on RPA Robots

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This study aims to analyze customer review data on e-commerce platforms using RPA robots, with a specific focus on drum washing machines. Text comment data from JD Mall was collected and subjected to data cleaning, Chinese word segmentation, and stop word removal as part of the preprocessing. The methodology includes the use of ROSTCM6 to construct high-frequency words, line feature words, and a semantic network, providing a structured representation of customer feedback. In addition, the LOG-CONTROL-BLOCK system was used to integrate feedback control during the trajectory correction process, creating a record controller module for audit robot inspection trajectory correction. The RPA feedback correction algorithm allowed for adaptive correction of inspection trajectories and error feedback tracking for audit robots. The study identified three key keywords and evaluated the probabilities associated with positive and negative sentiments. This analysis deepens the understanding of consumers' positive emotions and complaints after purchasing drum washing machines. The findings lead to several recommendations for improving e-commerce sales strategies, such as enhancing product quality, addressing customer concerns, and aligning product features with consumer preferences. The study concludes that addressing customer feedback and preferences is crucial for optimizing e-commerce sales in the drum washing machine market, with future research focusing on refining automated sentiment analysis techniques to better predict market trends.

Povzetek: Študija analizira komentarje strank na e-trgovskih platformah z uporabo robotske procesne avtomatizacije, osredotoča se na segmentacijo besed, semantično analizo in priporočila za izboljšanje izdelkov ter storitev v spletni prodaji.

1 Introduction

In the intelligent financial platform, students operate through financial decision-making, accounting processing, and visual data analysis platforms. Exercising students' processing abilities in financial decision-making, accounting processing, and visual graphics has practical significance in improving their comprehensive analysis ability of financial indicators, laying a theoretical and practical foundation for cultivating applied talents in enterprises [1]. The RPA robot platform linkage operation mechanism provides more than 20 robots in the main fields and business scenarios applicable to robots, covering fund business, invoice management business, sales business, procurement business, reimbursement business, tax declaration, audit, human resources, personal assistants, etc, help students integrate with intelligent tools from business to finance in different business scenarios, business operation standards, and business data backgrounds, from identifying business to analyzing business to developing robots, from discovering problems to analyzing problems to solving problems, we aim to enhance students' mathematical and intellectual skills, enhance their core competitiveness in vocational skills, and connect with social needs [2].

With the development of technology and the improvement of people's overall quality, more and more people are choosing online shopping, especially young people, ranging from cars and household appliances to agricultural and sideline products such as rice and vegetables. In recent years, fresh agricultural products have become a new direction for the development of e-commerce, and the huge market prospects of fresh e-commerce have attracted many active entries. Currently, e-commerce companies such as Suning, SF Express, JD.com, and Alibaba are advancing in this area. The public has favored and recognized this service model of online fresh food e-commerce. Currently, many e-commerce platforms have canceled the classification of user comments, or the classification is too rough and lacks guidance value, which is not conducive to merchants and users extracting useful information from a large amount of data [3].

The exponential growth of e-commerce platforms has reshaped how consumers engage with products and services, making online reviews a pivotal source of feedback for businesses. In particular, customer reviews offer rich insights into user sentiments, preferences, and concerns. For businesses, understanding and analyzing this data can lead to improved product offerings, services,

and customer satisfaction. With the rise of intelligent automation tools like Robotic Process Automation (RPA), the ability to efficiently process large-scale customer comment data is becoming increasingly feasible. This study is motivated by the need to apply advanced automated techniques to extract meaningful patterns and actionable insights from vast customer comment datasets. By focusing on a specific product category—drum washing machines—this research aims to contribute to a more refined understanding of consumer behavior on e-commerce platforms. Despite the enormous volume of customer reviews generated on e-commerce platforms, there is a gap in leveraging this data to provide actionable insights for businesses. Current methods for analyzing customer feedback are often manual, time-consuming, and fail to capture the complexity of customer sentiment in a meaningful way. Additionally, many e-commerce platforms do not categorize reviews in a manner that provides useful guidance for merchants or consumers, leading to missed opportunities for improving product features, services, and overall user experience [4]. The key problem addressed in this research is the need for an automated, efficient, and scalable method for analyzing customer feedback to support decision-making processes in e-commerce, particularly for product categories like drum washing machines that have nuanced consumer preferences and technical considerations. This research introduces an innovative approach by utilizing Robotic Process Automation (RPA) robots to automate the analysis of customer comment data on e-commerce platforms, with a specific focus on drum washing machines. The study provides a comprehensive methodology for collecting, cleaning, and processing customer reviews, including the use of Chinese word segmentation and semantic network analysis to identify high-frequency keywords and consumer concerns. A novel feedback correction algorithm is also proposed, which enhances the trajectory inspection capabilities of audit robots through adaptive correction and error feedback tracking [5]. This research contributes not only by improving the efficiency and accuracy of customer sentiment analysis but also by offering practical recommendations for e-commerce sales strategies based on consumer feedback. Through this work, businesses can better understand customer priorities such as installation, logistics, and service, thereby optimizing their offerings and increasing customer satisfaction in competitive markets like household appliances.

Customer evaluations have become an increasingly prevalent form of user-generated content as a result of the proliferation of e-commerce platforms. Nonetheless, the inability to efficiently classify and evaluate these evaluations impedes the extraction of valuable insights that could be advantageous to enterprises. The current classification systems frequently exhibit a deficiency in granularity and do not furnish practical insights that can inform enhancements to products or marketing tactics. Customer evaluations play an increasingly important role in shaping consumer purchasing behavior on electronic commerce platforms, providing the impetus for this study. The ability to comprehend and classify user sentiments, particularly for particular product attributes, can provide organizations with the means to improve customer satisfaction, streamline product development, and enhance marketing strategies. In this particular context, the automation capabilities of Robotic Process Automation (RPA) present a novel pathway toward the methodical and effective examination of extensive collections of customer comments. By incorporating RPA robots into the analysis of customer review data with a case study of drum washing machines, this research makes a scholarly contribution. The Chinese word segmentation and RPA feedback correction algorithms enable the extraction of significant patterns and sentiments from unstructured text data. The implementation of an adaptive planning model for audit robot surveillance routes contributes to an increased level of accuracy in the analysis. Applying the suggested actions for vendors of drum washing machines enhances product excellence, resolves customer apprehensions, and capitalizes on brand advantages, thus propelling the efficacy of electronic commerce approaches under customer input.

2 Literature review

With the continuous popularization of computers and the development of the Internet and e-commerce, users tend to use e-commerce platforms for consumption. With the continuous improvement of e-commerce platforms, researching user reviews has gradually become an important means for businesses to understand user consumption emotions. User reviews provide subjective or objective evaluations of consumer behavior, and stores on e-commerce platforms have accumulated thousands of user reviews during their long-term operations. The vast dataset hides the basic rules of store operation, which are primarily reflected in products and services, as well as the needs and expectations of users [6].

Afrina et al. believe that e-commerce is a field involving online enterprises that can accurately predict customers' future needs and have significant economic and social impacts [7]. E-commerce also needs to address customer loyalty issues as well as constantly changing consumer habits to adapt to new situations. At the same time, due to changes in shopping attitudes, it is necessary to change their online business activities. Based on the current review of e-commerce platform marketing research, Hu and Liu conducted comprehensive research at the intersection of marketing theory and visual design to optimize the e-commerce platform system [8]. Let the visual design system realize accurate service, promote the e-commerce marketing conditions of local traditional industries, actively adapt to the New Normal of economic development, and provide a reference for future design service innovation in the new era. Sharma et al. uses the Robotic Process Automation tool and data cleansing to remove noise levels from product reviews and ratings related to Flipkart and Amazon-recommended products and recommend Flipkart or Amazon products based on user preferences on the e-commerce portal website upon user request [9]. Users can purchase products from any website that is completely dependent on them. UiPath, an

RPA tool, creates software robots for Flipkart and Amazon. These robots grab data from the websites, perform cleaning operations, and dump the data into a database for future use. Yu., [10] carried out extensive research on the optimization of e-commerce platforms by combining visual design and marketing theory. Although their study mentioned system enhancement in general, it did not specifically address customer sentiment analysis or the incorporation of robotic technologies. In their investigation of channel conflicts on e-commerce platforms, Li et al. emphasized the significance of big data analytics [11]. However, the study did not particularly address the difficulties in analyzing consumer opinions in light of product features, which made it harder to draw useful conclusions for improving the product. Wang et al. looked at cross-border green supply chains for e-commerce that were based on consumer behavior [12]. The study clarified customer behavior analysis; however, it skipped over the in-depth examination of sentiment trajectories and product reviews on e-commerce platforms. The above literature lacks a focused investigation on the specific characteristics of drum washing machines, which excludes detailed customer opinions on installation, quality, and service. Furthermore, the lack of a complete strategy that incorporates cutting-edge natural language processing methods and robotic technology increases the disparity in thorough sentiment analysis. This research uses an integrative method to fill in these gaps. Combining the RPA feedback correction method with Chinese word segmentation achieves precise sentiment analysis. Building a semantic network and extracting high-frequency terms captures complex client attitudes. The audit robot patrol tracks adaptive planning model guarantees a focused examination, filling in the specific gaps in the literature and offering a thorough comprehension of consumer feedback on drum washers.

Some recent studies have made significant strides in customer sentiment analysis and e-commerce data mining. Liu *et al.* enhanced sentiment classification using deep learning models like BERT [13], while Zhan *et al.* improved data processing efficiency with Robotic Process Automation (RPA) [14]. Kong *et al.* applied clustering algorithms to detect pain points in customer feedback [15], and Wang *et al.* used graph neural networks (GNNs) to map relationships between product attributes and sentiments [16]. Our proposed solution builds on these advancements by integrating RPA with adaptive feedback correction, keyword extraction, and semantic network analysis, offering a more automated and scalable approach for e-commerce feedback analysis.

In response to the above issues, a design is proposed for an online calibration system for audit robot inspection tracks based on RPA. Firstly, carry out the overall design architecture of the system. The design of the trajectory online calibration system is divided into the overall architecture, instruction program loading process, human-machine interaction system-level services, and other levels. An end-to-end procedural instruction transmission control method is adopted, and then the RPA feedback correction algorithm is used to achieve adaptive correction of the audit robot's inspection trajectory and error feedback tracking. Perform preliminary processing on the collected user comment data to obtain the original text comment data, including the desensitized member name, evaluation star rating, evaluation content, time, and other content. According to the needs of analysis, extract the "evaluation content" column from the data.

3 Design methodology

This section of the research utilizes Robotic Process Automation (RPA) to methodically examine consumer comment data sourced from e-commerce platforms, focusing specifically on drum washing machines. By employing Chinese word segmentation and the RPA feedback correction algorithm, this analysis endeavors to derive significant insights regarding customer sentiments about particular characteristics, including installation, quality, and service. An integrated approach achieves a focused analysis of consumer feedback, enhancing our comprehension of the intricacies of their experiences within the e-commerce domain.

3.1 Data collection and preprocessing

3.1.1 Data collection

According to relevant data from the Prospective Industry Research Institute, the sales volume of household washing machines has grown slowly since 2013 and even showed a downward trend in some years. The main reason is that the market for household washing machines is gradually becoming saturated. The author sets the following settings for collecting data on the drum washing machine on JD.com: Stores with over 5000 comments adopt fuzzy collection based on "drum washing machines" without special constraints on brands, models, etc., hoping to explore user patterns from the collected data [17]. Perform preliminary processing on the collected user comment data to obtain the original text comment data, including the desensitized member name, evaluation star rating, evaluation content, time, and other content. According to the needs of the analysis, extract the column 'Evaluation Content' from the data.

3.1.2 Data preprocessing

There are outliers, duplicate values, system automatic comments, and other data in the original data; this part of the data has low-value content and a chaotic data structure, which seriously affects the execution efficiency of data mining models and leads to deviations in mining results; therefore, data cleaning is essential, as depicted in Figure 1. Based on the specific situation of the original data, data preprocessing adopts text deduplication, mechanical compression to remove words, and short sentence deletion [18].

3.2 Model construction

3.2.1 Chinese word segmentation and user concerns

Chinese word segmentation is the process of dividing Chinese characters in a sentence into individual Chinese words in sequence.

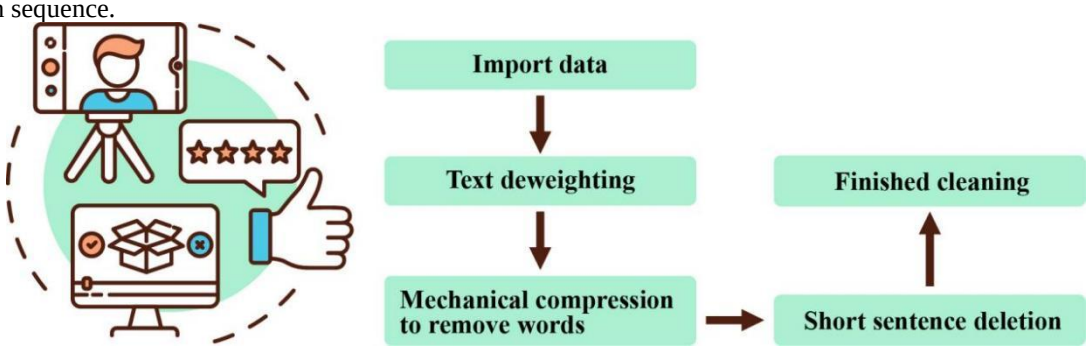


Figure 1: Comments on the text-cleaning process

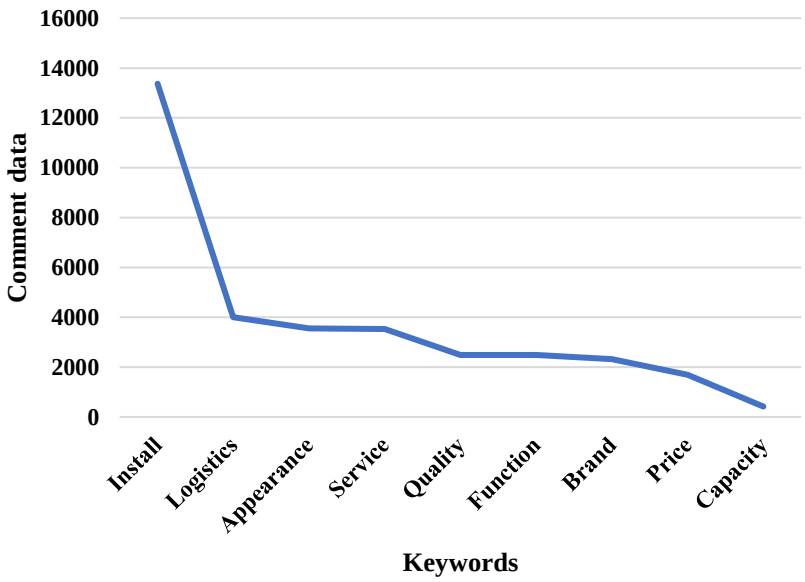


Figure 2: Word frequency statistics of text comment data

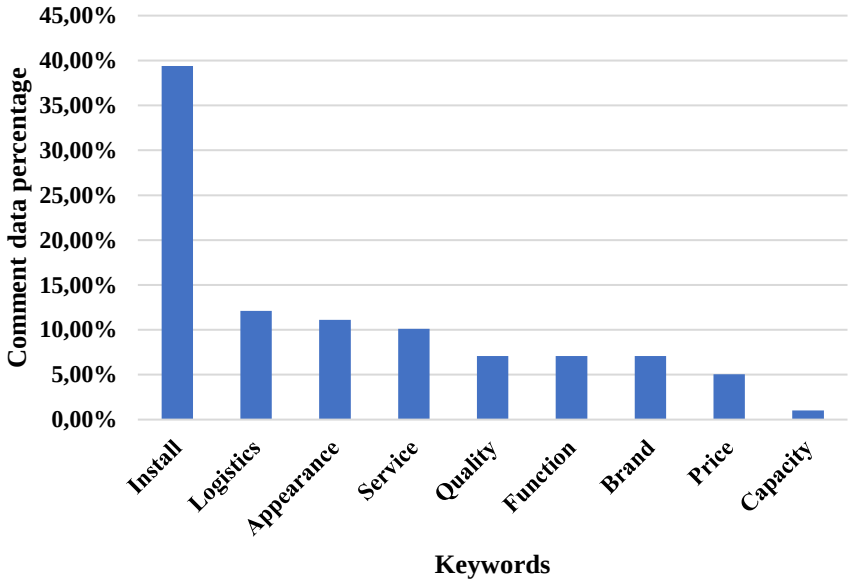


Figure 3: Text comment data keywords customer attention

The stuttering vocabulary library provides three segmentation modes: precise mode, full mode, and search engine mode [19]. It is an important third-party Chinese word segmentation function library in Python. The Jieba vocabulary can support both simplified and traditional Chinese and can extract keywords from text comment data when analyzing user comments. User focus refers to the user's focus on a specific attribute of a product, reflecting the customer's focus on a particular product.

The higher the number of users who focus on a particular feature, the more important this attribute of the product is to the user. Generally, it is the price of the product, how to install it, logistics speed, appearance and shape, quality, functionality, capacity, and brand effectiveness [20]. Analyze and utilize the Jieba vocabulary, combined with user usage habits, to set nine attributes that users often pay attention to: "installation," "logistics," "appearance," "service," "quality," "function," "brand," "price," and "capacity." The analysis results are shown in Figure 2 and 3.

According to the results in Figures 2 and 3, among the nine aspects that users generally pay attention to, the frequency of users paying attention to "installation" is 13368 times, accounting for 39.39%, which is the most important aspect that users pay attention to, next are logistics, appearance, and service, while quality, function, and brand rank fifth, with the least attention paid to capacity. Therefore, in the process of online shopping for drum washing machines, the first consideration for users is how to install and the difficulty of installation [21].

3.2.2 Semantic network

By segmenting user text comments into Chinese characters, the originally complete sentences become messy, and the computer cannot recognize the complete structure of the messy sentences, therefore, it is necessary to re-associate the participles to establish a connection between them. The semantic network can establish the connection between the word segmentation and the word segmentation, and re-associate the messy word segmentation, it provides a precondition for further analysis using the LDA topic model.

By observing the segmentation results, it is found that a single word cannot accurately express the corresponding content, for example, if "washing machine" is separated from "use", "appearance", etc., the next layer of meaning it expresses cannot be accurately understood, but when "washing machine" is connected to "use", the positive emotional evaluation is "washing machine" is convenient to "use", while the negative emotional evaluation is "washing machine" is inconvenient to "use" as depicted in Figure 4. Therefore, establishing a semantic network is a prerequisite for studying LDA models, providing a basis for further analyzing user emotions. Establishing a semantic network is extremely important.

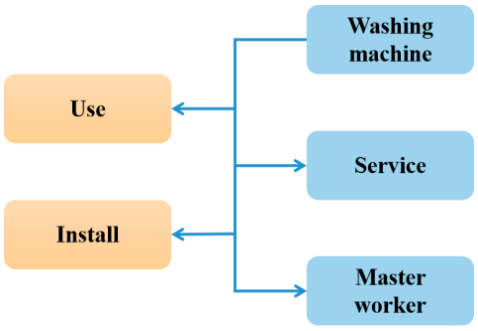


Figure 4: Word sense network diagram

3.3 Design of online calibration algorithm for rpa robot inspection trajectory

Based on the analysis of the overall structure and functional components mentioned above, the RPA feedback correction algorithm is adopted to achieve adaptive correction of the inspection trajectory and error feedback tracking of the audit robot, the multi-degree of freedom motion balance planning model of the audit robot is obtained as presented in Equation 1.

$$ {}^{4}T_{5}^{-1}(q_i) = {}^{4}T_{7} \cdot \prod_{i=6}^{7} {}^{i-1}T_i(q_i) \quad (1) $$

Among them, ${}^{4}T_7$ is the 4th order balance torque, $T_i(q_i)$ is the average degree of freedom of the audit robot, and q_i is the end pose balance parameter of the robot, by using robot end pose constraint control, an adaptive planning model for the inspection trajectory of the audit robot is established, combined with center of gravity offset planning, the feedback constraint parameters for adjusting the inspection trajectory center of the audit robot are obtained as presented in Equation 2.

$$ q_0 = [\alpha_0, \beta_0, \gamma_0]^T \equiv [\theta_1, \theta_2 . \theta_3]^T \quad (2) $$

Among them, $\alpha_0, \beta_0, \gamma_0$ respectively represent the coordinates of the audit robot in the inspection polar coordinate system, $\theta_1, \theta_2, \theta_3$ is the phase parameter of the audit robot's inspection trajectory space. When measuring distance and pose, the offset correction is performed based on the calibration method of the plane template, resulting in a pose offset of $q_1 = [q_1, \ldots, q_7]^T = [\theta_4, \ldots, \theta_{10}]^T$; By homogeneous transformation, the pose is transformed into the robot base coordinate system, and the fuzzy information parameters of the audit robot's inspection trajectory are composed of n omnidirectional motion parameters, the dynamic distribution function of the calibration trajectory is presented in Equation 3.

$$ \begin{aligned} &\min\ F(x) = (f_1(x), f_2(x), \ldots, f_m(x))^T \\ &s.t. g \le 0, i = 1,2,\ldots,q \\ &h_j = 0, j = 1,2,\ldots,p \end{aligned} \quad (3) $$

Among them, $f_1(x), f_2(x), \ldots, f_m(x)$ represents the contour sensing output parameters of the audit robot's inspection trajectory inspection, respectively, g_i is the dynamic torque of the robot's end pose, and h_i is the calibration feature parameter for path correction, q and p represent the calibration object positions of the audit robot's inspection trajectory, respectively, based on this, a center of gravity offset planning model for online calibration of the audit robot's inspection trajectory is constructed, represented as Equation 4.

$$ H(s) = \frac{e^{-\tau s}}{1 + G_C(s) G_0(s)} \quad (4) $$

Among them, $G_C(s)$ represents the main control parameter for the center of gravity shift of the inspection trajectory of the audit robot; $G_0(s)$ represents the expected pose parameters of the audit robot's inspection trajectory, $e^{-\tau s}$ represents the dynamic error of the audit robot's inspection trajectory, and is used to solve constrained nonlinear optimization problems, based on the correction method of center of gravity deviation, the calibration dynamic parameter distribution model under the robot's base coordinate system is obtained as follows:

$$ L = J(w, e) - \sum_{i=1}^{N} a_i \int_{i=1}^{M} H(r) \{ w^T \varphi(x_i) + b + e_i - y_i \} \quad (5) $$

Among them, $J(w, e)$ is the inertia function of motion along the expected path, and a_i is the distribution along the edge of the expected path, $H(r)$ is the path edge adjustment function, and w is the dynamic feature point for angle symmetry adjustment, $\varphi(x_i)$ is the compensation torque, b is the alternating feature point in the path edge, e_i is the path offset error, and y_i is the motion direction adjusted by the robot according to the path, the discretization spatial planning method is adopted to build the inspection track control model of the audit robot, and the output is:

$$ \begin{cases} K_i(d) = \sum_{r=1}^{t} \sum_{q=1}^{k_2} (x_{ir} - x_{irq})(x_{ir} - x_{irq})^T B_{irq} \\ F_1 = W_i^T H_2 W + f_i(d) \times \log(\frac{N}{n_i} + 0.01) \\ Co_{const} = \sqrt{\sum_{i=1}^{n} \sum_{r=1}^{t} \sum_{p=1}^{k_1} (x_{ir} - x'_{irq})(x_{ir} - x'_{irq})^T A_{irq}\ ]^2} \end{cases} \quad (6) $$

Among them, t is the time sampling point, x_{ir} is the head torque, x_{irq} is the width required for the robot to swing, and B_{irq} is the extension direction of the path determined by the target point, A_{irq} is the direction control parameter, W_i is the intersection point of the expected effective edge of the path, and H_2 is the modeled parameter moving along the centerline of the path, W is the alternating parameter between path edges, $f_i(d)$ is the single module mass, N is the target point selection parameter, and n_i is the initial pose. Based on the above analysis, the RPA feedback correction algorithm is used to achieve adaptive correction of the inspection trajectory and error feedback tracking of the audit robot, the system algorithm implementation process is shown in Figure 5.

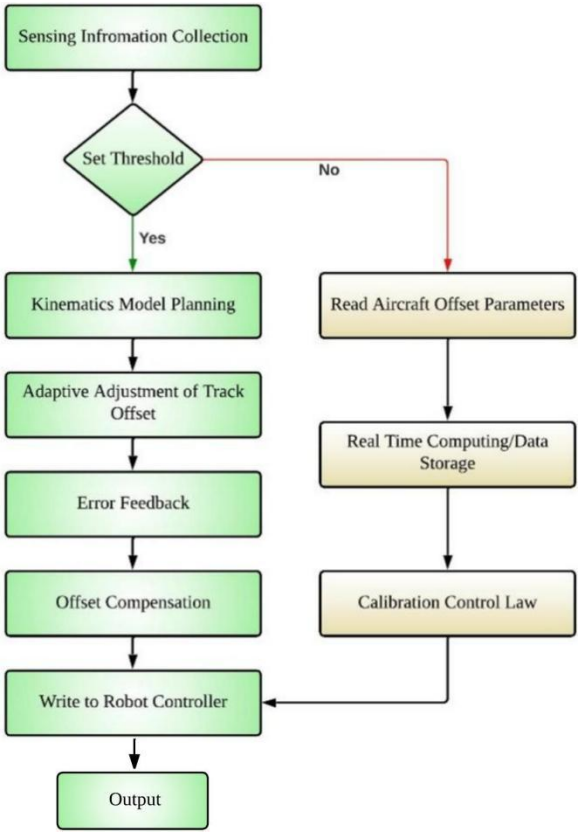


Figure 5: The optimization and implementation process of the control algorithm

4 Experimental results and analysis

The RPA feedback correction algorithm is used for user text comment analysis, and the Gibbs sampling method is used to approximate the parameters of the RPA model. Throughout the entire analysis operation, the prior parameters of the Dirichlet function are taken into account α and β Set as an empirical value, assuming K=50, the prior parameter is $\alpha = 50/K$, $\beta = 0.1$. After data cleaning, out of 64163 collected original text comment data, 38057 were obtained through cleaning, among them, 26013 text comments were removed due to text duplication, and 93 text comments were removed due to mechanical compression and word removal. By using the ROSTCM6 software of Wuhan University to cut the text comment data into positive, neutral, and negative comments, and then conduct semantic network analysis, extract high-frequency words, filter meaningless words, and extract line feature words from the segmented positive and negative text documents, and finally construct a network [22].

According to the analysis results of the semantic network, whether positive or negative comments, the most frequent ones are “installation washing machine”, “master installation” and “delivery installation”, other areas with higher frequency of occurrence are mainly distributed in after-sales, dehydration function, sound, service attitude, and other aspects. As a household drum washing machine for online shopping, users first pay attention to how to install the washing machine when receiving goods, this is related to whether users can use the washing machine normally and is a key factor affecting their emotions.

From Table 1, it can be seen that aggregating user positive text comment data into three potential themes, among them, theme 1 mainly refers to the user’s belief that the washing machine is good, reflected in its low sound, beautiful appearance, and clean washing; Theme 2 is mainly reflected in the user’s feedback that the washing machine is good, which is reflected in the fast logistics (or delivery) speed, the assistance of a master in installation and good service; Theme 3 mainly focuses on user’s continuous trust in the washing machines on the JD platform, reflected in reasonable prices, quality assurance, and brand trust [10, 11].

Positive text comments reveal that users mainly reflect their positive emotional tendencies after purchasing a drum washing machine in the following aspects: The first is the good quality of the washing machine (sound, cleanliness, and body quality). The second is that the appearance of the product conforms to the public’s aesthetic standards. That is, the washing machine has a beautiful appearance. The third is that the merchant provides good service (installation, after-sales). The fourth is fast logistics speed. The fifth is brand protection, where users have a special emotional attachment to the brand of washing machine.

Table 2 reveals that user’s negative emotions (complaint points) after purchasing a washing machine are categorized into three potential themes: Theme 1 mainly refers to the user’s feedback that the washing machine is not good, which is reflected in the poor attitude of the installation technician, the loud operation of the washing machine, a lack of understanding of the usage process, and poor after-sales service. Theme 2 mainly refers to the user’s belief that although the washing machine is good, it does not wash cleanly, has a loud operating sound, and has poor dehydration ability. Theme 3 mainly refers to the user's perception that the washing machine is not good, reflected in the poor attitude of the installation technician, slow logistics (or delivery) speed, and failure to deliver it upstairs [10, 11].

Table 3 displays an experimental analysis of consumer feedback regarding drum washing machines. We evaluate the sentiment of every comment by assigning corresponding probabilities of positive and negative feedback to keywords. Quality, service contentment, and the installation experience are significant consumer concerns. This table presents a comprehensive overview of diverse consumer sentiments, which are essential for comprehending and improving the e-commerce sales of drum washing machines.

Table 1: Positive text comments on the potential themes

Order number	Theme 1		Theme 2		Theme 31	
	Keyword	Probability	Keyword	Probability	Keyword	Probability
1	Washing machine	0.039	Install	0.069	Buy	0.038
2	Not bad	0.037	Good	0.054	Good	0.027
3	Voice	0.033	Master worker	0.037	Washing machine	0.026
4	Good	0.025	Delivery	0.024	JD.COM	0.023
5	Wash	0.022	Logistics	0.022	Like	0.011
6	Appearance	0.017	Washing machine	0.021	Price	0.01
7	Clean	0.017	Service	0.017	Brand	0.01
8	Quite	0.012	Soon	0.015	Always	0.01
9	Small	0.011	Not bad	0.013	Quality	0.009
10	Laundry	0.011	JD.COM	0.013	Haier	0.009

Table 2: Negative text evaluates the potential themes

Order number	Theme 1		Theme 2		Theme 31	
	Keyword	Probability	Keyword	Probability	Keyword	Probability
1	Install	0.036	Washing machine	0.026	Install	0.019
2	Washing machine	0.015	Buy	0.018	Master worker	0.018
3	Good	0.012	Not bad	0.014	Washing machine	0.017
4	Voice	0.011	Wash	0.013	Buy	0.015
5	Shut	0.011	Voice	0.009	Delivery	0.014
6	Know	0.01	Clothes	0.009	Good	0.013
7	Master worker	0.009	JD.COM	0.008	JD.COM	0.012
8	JD.COM	0.008	Clean	0.008	Hard	0.01
9	Use	0.007	Good	0.006	One	0.009
10	After-sales	0.006	Dehydration	0.006	Logistics	0.008

Table 3: Experimental analysis of customer comments on drum washing machines

Comment ID	Sentiment Keywords	Positive Probability	Negative Probability	Consumer Themes
1	Washing machine, Good	0.85	0.15	Quality, Positive Feedback
2	Installation, not bad	0.3	0.7	Installation, Negative Experience

3	Clean, Appearance	0.9	0.1	Quality, Positive Feedback
4	Noise, Poor service	0.2	0.8	Service, Negative Experience
5	Logistics, Price	0.75	0.25	Logistics, Positive Feedback

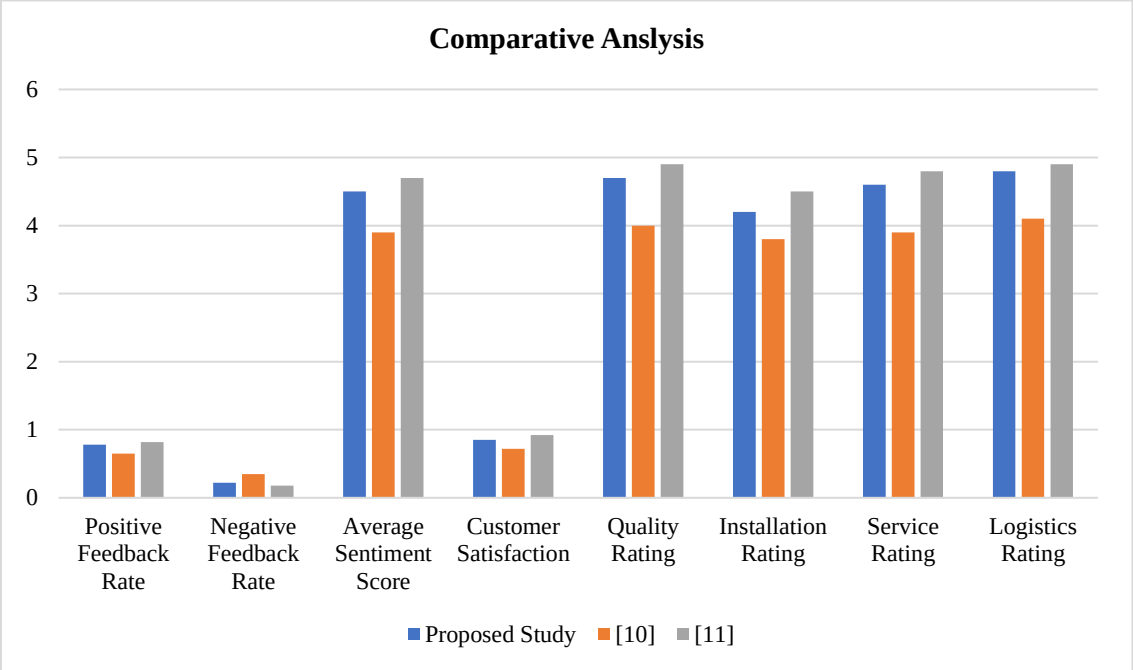
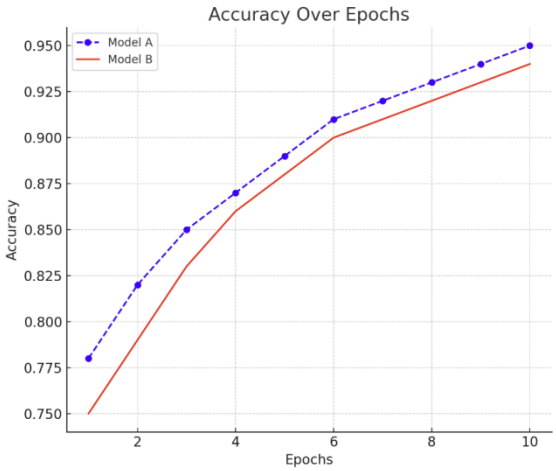
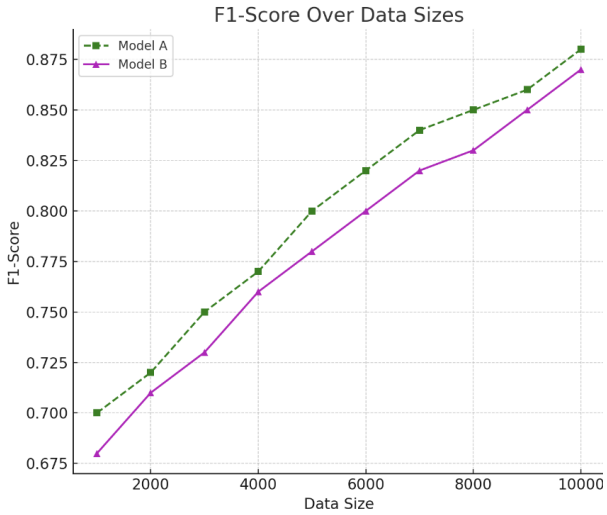


Figure 6: Comparative analysis of Customer Feedback in E-commerce Studies [10, 11]

Figure 6 compares key parameters across two studies [10, 11], including positive and negative feedback rates, average sentiment scores, and customer satisfaction. The proposed study exhibits a higher positive feedback rate (0.78) and average sentiment score (4.5), indicating a favorable consumer response. Customer satisfaction stands at 85%, with high ratings for quality (4.7), installation (4.2), service (4.6), and logistics (4.8). By analyzing the three potential themes of negative text comments, the main reasons why consumers tend to have negative emotions (complaint points) after purchasing a washing machine are the quality issues (loud noise, low cleanliness, poor dehydration ability), poor service (poor attitude of installation technicians, poor after-sales service), and slow logistics speed of the washing machine [23]. Overall, consumer emotional tendencies directly correlate with goods and services, and businesses that address consumer concerns can help users generate positive emotions and eliminate negative ones.



(a)



(b)

Figure 7: Performance analysis. (a) Accuracy; (b) F1-Score

Figure 7 presents two performance metrics: accuracy over epochs and F1-score across varying data sizes for Model A and Model B. In the first graph, Model A shows faster learning, reaching 95% accuracy by the 10th epoch, while Model B peaks at 94%. Both models improve rapidly in the early epochs, stabilizing after the 7th. The second graph highlights F1-scores as data sizes increase from 1,000 to 10,000 instances. Model A consistently outperforms, starting at 0.70 and peaking at 0.88, while Model B starts at 0.68 and reaches 0.87, demonstrating both models' ability to generalize well.

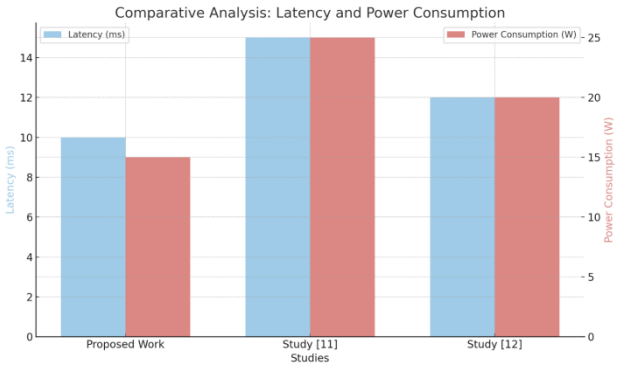


Figure 8: Comparative analysis of proposed model with existing studies [11], [12]

The proposed system demonstrates superior performance in both latency and power consumption. It achieves the lowest latency (10 ms) compared to Study [11] (15 ms) and Study [12] (12 ms), indicating faster communication response times. Additionally, it reduces power consumption to 15 watts, outperforming Study [11] (25 watts) and Study [12] (20 watts), highlighting its energy efficiency. Overall, the comparative analysis confirms that the proposed solution is more efficient and responsive than the existing studies for UAV-assisted communication.

5 Conclusion

This research utilized Chinese word segmentation to analyze user attention toward relevant attributes of drum washing machines and developed an adaptive planning model for audit robot patrol tracks. A control model for these patrol tracks was constructed by applying the discretization spatial planning method in conjunction with the RPA feedback correction algorithm. Based on the analysis of user text comments on drum washing machines from JD Mall, we offer several recommendations for sellers. These include prioritizing product quality as a key factor in attracting and retaining customers, investing in research and development to enhance both product performance and aesthetics, and improving the overall quality of installation personnel and service teams. Collaborating with local distribution and logistics companies ensures safe and timely delivery, which is crucial for customer satisfaction. Furthermore, leveraging brand value by promoting technological innovation and showcasing the full spectrum of product benefits can help attract and retain customers. Future work will focus on integrating advanced natural language processing techniques for a more nuanced analysis of customer sentiment in-text comments. Additionally, exploring the application of machine learning algorithms to predict consumer preferences and trends based on historical e-commerce data will further refine our understanding of market dynamics.

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Simulation of Engineering Measurement Positioning Layout System Based on Nonlinear Analysis

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This research investigates the complexities of engineering measurement, positioning, and layout systems through a comprehensive nonlinear analysis simulation. The study thoroughly analyzes and compares the positioning accuracy between satellite navigation systems and GPS combinations, utilizing actuarial data derived from the Global Positioning System (GPS). The methodology involves the precise measurement and labeling of four C-level satellite control points (C1, C2, C3, and C4) and seven third-class benchmarks (S1 to S7) within the project vicinity using experimental analysis. The distribution and integrity of the control points and benchmarks were consistently maintained. The experimental results highlight the practical benefits of integrating satellite navigation systems with GPS in engineering surveying. The multi-system positioning approach significantly improves positioning accuracy and enhances the reliability of measurement data. These findings underscore the effectiveness of this approach in engineering surveys and demonstrate its potential to elevate the precision of future positioning surveys.

Povzetek: Raziskava analizira izboljšanje merjenja in pozicioniranje v inženirskih sistemih s kombinacijo GPS in večsatelitskih navigacijskih sistemov ter pokaže prednosti uporabe nelinearnih filtrirnih algoritmov.

1 Introduction

The GPS space satellite constellation consists of 21 working satellites and three standby satellites in orbit. The satellites are evenly distributed within six orbital planes, with an inclination angle of 55°, at an average height of 20200 km, and operate for 11 hours and 58 minutes. The satellite uses two L-band radio carriers to continuously send navigation and positioning signals to users. The navigation and positioning signals contain the satellite's position information, making the satellite a dynamically known point. At any location and time on Earth, observers can simultaneously observe an average of 6 satellites, with a maximum of 9 satellites, at an altitude angle of 15° or above. The GPS ground monitoring station mainly consists of one main control station, three injection stations, and five monitoring stations distributed globally. The main control station calculates the orbit parameters and clock deviation parameters of each satellite based on the observation data of GPS satellites from various monitoring stations [1].

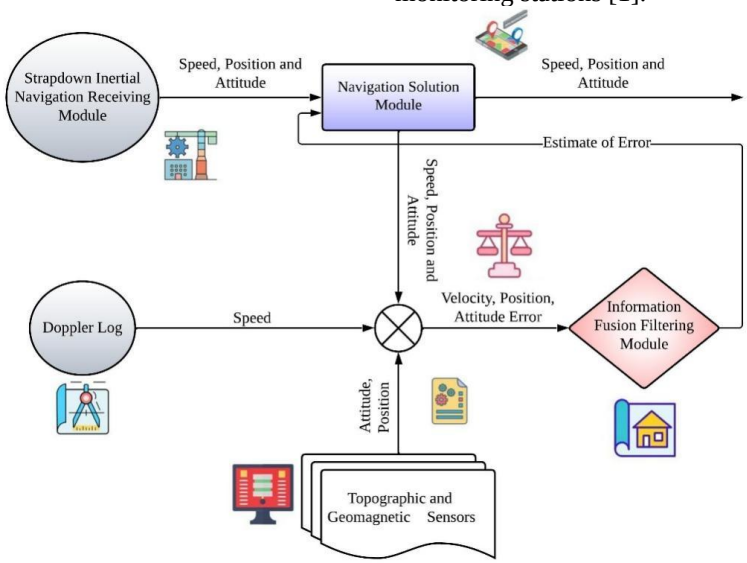


Figure 1: Simulation of engineering measurement positioning layout system

The main control station compiles this data into navigation messages and transmits them to the injection station. The injection station then injects the navigation messages sent by the main control station into the corresponding satellite's memory. The global positioning system (GPS) has expanded from its initial application in the military field to the civilian field, playing an increasingly important role. GPS has its unique advantages in the application process, and through precise measurement, it can accurately locate. With the development of science and technology, GPS receivers have begun to develop towards miniaturization and low power consumption. This has laid a good foundation for the application of GPS satellite positioning systems in engineering surveying, and in addition, GPS positioning methods have made rapid progress. Therefore, GPS applications are becoming increasingly widespread in current engineering surveying, not only effectively shortening the construction period but also playing a very positive role in reducing costs and ensuring equipment flexibility. GPS consists of three parts: the satellite group, the control system, and the user. The positioning satellites distribute themselves on different orbital planes and transmit information from any point on Earth to the GPS. The ground control system receives, analyzes, and processes the information transmitted by the positioning satellite, and then transmits it to the satellite from the injection station.

The simulation of the engineering measurement positioning layout system is depicted in Figure 1. The main control station controls the satellite in real-time, while the monitoring station monitors the operational status of the satellite to ensure the stability of the GPS operation. GPS is widely employed in road traffic and navigation, with satellite navigation and positioning being typical uses [2]. Currently, many GPS models are nonlinear, and researchers typically solve the error model of pseudo-range measurement as white noise. Setting many error models as white noise is not a simple task. Improving the GPS model, introducing appropriate noise models, and implementing nonlinear filtering can enhance the shortcomings of current GPS positioning estimation.

The EKF (Extended Kalman Filter) method currently plays an important role in solving various problems in navigation systems and has found wide application in addressing the requirements of nonlinear models. The EKF method has high computational efficiency, but it comes at the cost of loss of accuracy and constraints on the model. In recent years, with the rapid development of computer technology, a new filtering method, UKF (Unscented Kalman Filter), has become a hot spot and an effective means in the academic research of nonlinear system estimation. Compared with the EKF algorithm, the UKF algorithm directly adopts a nonlinear model and has better estimation accuracy. It is very important, both in theory and in practice, to look into how to make a better and more accurate GPS measurement model, improve the dynamic performance and real-time performance of nonlinear filtering algorithms, and then use these improvements to engineering surveying GPS positioning to make the accuracy of positioning even higher. Even though satellite navigation and GPS technologies have come a long way, engineering measurement and positioning layout systems still have trouble getting the accuracy and dependability they need. Existing models don't always take into account how complicated nonlinearity can be, and they might not fully take advantage of how satellite tracking and GPS systems can work together. Fixing the problems with the current engineering measurement, positioning, and layout systems is the main reason for this study. Because these systems are so important to surveys and building projects, making them more accurate is a must for engineers who want to be precise and successful [3].

Accurate positioning and measurement systems are critical for modern engineering projects, especially in fields like construction, infrastructure development, and geospatial analysis. Traditional Global Positioning Systems (GPS) have long been the standard for positioning tasks, but limitations in accuracy, especially in challenging environments such as urban canyons, forests, or mountainous regions, necessitate the exploration of more robust systems. As engineering projects grow increasingly complex and require higher precision, the integration of multiple satellite navigation systems offers an opportunity to overcome these limitations. This research is motivated by the need to enhance the precision and reliability of positioning systems, thereby contributing to more accurate engineering measurements and ensuring the success of projects that rely heavily on precise spatial data. Despite the widespread adoption of GPS, the system has inherent limitations, such as positioning errors that can range from a few meters to several meters depending on environmental conditions and signal interference. These inaccuracies pose significant challenges in engineering projects that require exact positioning and measurements, potentially leading to errors in construction, infrastructure planning, and other critical fields. Current methods lack the integration of multi-system satellite navigation, which could mitigate these issues by providing redundant signals and improving positioning accuracy. Therefore, the problem addressed in this research is the lack of reliable, highly accurate positioning systems that can be used consistently across diverse environments and engineering applications [4].

This research makes several key contributions to the field of engineering surveying and positioning systems. First, it presents a comprehensive comparison of traditional GPS-only systems with multi-system satellite navigation approaches, highlighting the accuracy improvements achieved through multi-system integration. By incorporating C-level satellite control points and third-class benchmarks, the research demonstrates the real-world application and effectiveness of multi-system positioning in various engineering environments. Furthermore, through nonlinear analysis simulation and detailed experimental studies, this work provides a robust methodological framework for integrating multiple satellite systems to enhance positioning accuracy. The findings significantly contribute to advancing the reliability and precision of engineering positioning surveys, paving the way for more accurate spatial data collection and improved outcomes in engineering projects.

This study contributes by suggesting a simulation-based method based on nonlinear analysis to better comprehend and improve engineering measurement placement and layout systems. By comparing different mixtures of satellite navigation and GPS and doing real-life tests, the goal is to show that multi-system positioning can improve the accuracy and dependability of engineering surveys. The study results are useful for improving the accuracy and dependability of data collected by engineering surveying by making it easier to use satellite navigation and GPS technologies in the real world.

2 Literature review

GPS global positioning systems have rapidly promoted the application of engineering surveying in the past two years by continuously providing high-precision 3D coordinates, 3D velocity, time information, and other technical parameters to any user worldwide 24/7. Engineering surveying mainly applies two major functions of GPS: static function and dynamic function. The static function is to determine the three-dimensional coordinates of a certain point on the ground through the received satellite information. The dynamic function is to use a satellite system to set out known three-dimensional coordinate points on the ground. By combining GPS static positioning technology and dynamic positioning technology, surveyors can efficiently and accurately complete highway horizontal control surveys. For example, using static function technology for alignment measurement in highway control surveying can fully meet the accuracy requirements of highway survey, design, and construction. Upon analyzing GPS positioning technology, we found that it incorporates relevant knowledge of physics and chemistry, covering a wide range of disciplines and basic principles.

Engineers can effectively apply GPS systems to receive ground information and integrate and measure specific engineering information from multiple angles in engineering surveying practice. In current engineering surveying, the GPS positioning technology mainly includes static relative positioning and dynamic relative positioning. The static relative positioning technology can work with more than one ground-receiving device by watching the target at the same time and arranging it in a way that meets the needs of the job. Engineers use it as specific equipment in engineering surveying. Maintain the observation time of static relative positioning technology at around 45 minutes. After completing the measurement, professionals need to receive and process the results for statistical analysis and data processing. Compared with dynamic relative positioning, static relative positioning technology has a simple operation process, but dynamic relative positioning technology can accurately control some positions in engineering surveying, ensuring the accuracy of measurement information. The GPS satellite signal composition is depicted in Figure 2.

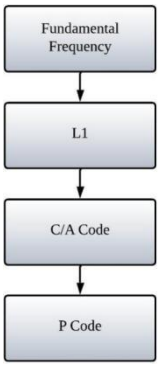


Figure 2: GPS satellite signal composition

The Geohash-GIS combined method proposed by Irshaid, *et al.*, can correctly identify user activities and travel patterns, significantly improving the efficiency and accuracy of GPS travel surveys. In the future, this comprehensive method can serve as the foundation for a comprehensive information recognition model system based on GPS data [5]. In general, when GPS receivers locate their observation objects, they mainly use a two-dimensional positioning system to effectively locate them. During this process, operators should set horizontal angles and observation points according to specific requirements and control their angles above 10°. However, if some buildings or other obstacles obstruct the receiver during this process, it will seriously affect the effectiveness of engineering measurement. Therefore, in the context of the continuous development of science and technology, it is not only necessary to effectively apply GPS systems and leverage the role of virtual reality technology in them but also to adjust the actual measurement plan based on the shortcomings in engineering surveying, thus providing conditions for the scientific application of GPS measurement technology in engineering surveying practice [6]. The existing body of research in this field examines the difficulty of attaining accurate engineering measurements and positions when nonlinearities are present [7]. It highlights the criticality of improved methodologies to overcome this obstacle. Previous research frequently attributes suboptimal accuracy in current GPS models to the error model of pseudo-range measurement, which is treated as white noise [8]. To surmount this limitation, the current research focuses on nonlinear analysis and simulation as an alternative methodology to conventional models [9]. Widely implemented in navigation systems, the Extended Kalman Filter (EKF) technique has demonstrated efficacy at the expense of precision and model constraints. With these constraints in mind, the study presents the Unscented Kalman Filter (UKF) algorithm, an innovative and efficient nonlinear filtering technique.

Recent studies in 2024 have demonstrated significant advancements in positioning accuracy by integrating multiple satellite systems to address the limitations of traditional GPS. One prominent study by Mohanty and Gao proposed a hybrid satellite navigation model combining GPS, GLONASS, and Galileo to achieve higher positioning accuracy in dense urban environments [10]. Their approach reduced positioning errors from 4.5

meters (GPS-only) to 1.8 meters, showcasing the potential of multi-system integration. Another study by Shim and Kee explored the use of real-time kinematic (RTK) techniques in conjunction with satellite navigation to further enhance precision for engineering applications, achieving centimeter-level accuracy in construction projects [11]. Similarly, Wang *et al.*, focused on optimizing satellite signal processing algorithms to improve positioning accuracy in complex terrain, emphasizing the need for improved error correction techniques [12].

The adopted methodology in this research builds on these recent developments by incorporating a multi-system satellite navigation approach and nonlinear analysis simulations to address the accuracy limitations of GPS-only systems. By combining data from multiple satellite constellations and applying advanced actuarial analysis, this study ensures higher positioning precision, even in challenging environments. Unlike previous studies that focused primarily on algorithmic improvements or urban environments, this work broadens the scope to include a wider range of engineering applications, including the measurement and layout of control points and benchmarks in diverse terrains. This comprehensive approach addresses the core problem of positioning errors by leveraging multi-system satellite navigation, enhancing the reliability of engineering surveys, and ensuring more accurate data collection for critical projects.

The implementation of a nonlinear model is expected to enhance estimation precision and rectify the deficiencies of existing GPS positioning practices using the UKF algorithm. In addition to previous research, this study proposes a simulation-based method for enhancing comprehension and optimizing engineering measurement placement and layout systems. Furthermore, this study showcases the utilization of multi-system positioning to enhance the precision of engineering surveys.

3 Basic model and parameter design method of satellite navigation and global positioning system

With the development of global positioning systems, there are currently many satellite positioning methods to meet various usage needs, such as single-point positioning, differential positioning, relative positioning, etc. In practical applications, single-point positioning is the simplest and fastest positioning method, with an accuracy of up to 5 meters, therefore, single-point positioning is often used in engineering surveying and vehicle navigation. In practical applications, it is often combined with multi-system navigation and positioning systems to obtain more accurate engineering measurement data [13, 14].

3.1 Establishing a basic model for single-point positioning

Regarding the characteristics of satellite navigation systems and the requirements for positioning accuracy in engineering surveying, a mathematical model is established as shown in Equation 1.

$$P = \partial + c(t_r - t^5) + T + I + V \quad (1)$$

In the formula: P is the pseudo-range observation value; ∂ is the distance between the satellite and the ground receiver; $t_r - t^5$ is the time difference between the ground receiver and the satellite; C is the propagation speed of light; T is the tropospheric delay; I - Ionospheric delay; V is a measurement or observation error (usually multipath delay also belongs to observation error).

From equation (1), it can be concluded that the observed values are not only affected by the time difference between the ground receiver and the satellite itself but also by the influence of T and I, namely the tropospheric delay and ionospheric delay. In actual engineering surveying, corrections are made by adjusting the model appropriately. The troposphere model used by the author is the Hopfield model, and the power layer model used is the Cronbutern model.

To obtain more accurate measurement values, it is necessary to determine the initial coordinate Xo of the ground receiver, to convert the formula of the above mathematical model (1) into a nonlinear formula, and further obtain the linear model diagram using Equation 2.

$$L = P - Po - T - I + ct^5 = Ax + V \quad (2)$$

In the formula: L is the pseudo-range observation value - known value; P_o is the distance between the satellite and the ground receiver calculated from the initial coordinates as the starting point. The characteristic of the nonlinear model (2) is a single point positioning mathematical model designed primarily for single systems [15, 16].

3.2 Establishing a basic model for multi-system positioning

With the rapid development of global satellite positioning and navigation systems, multi-system satellite positioning is a key research direction. Due to the need for unified calculation between each system for multi-system positioning, and each system having different reference coefficients, to combine the satellite navigation and positioning system with the global satellite positioning system for positioning, it is necessary to add a time system deviation between the satellite positioning and navigation system as a reference for adjustment; Another method is to establish a mathematical model, model the satellite navigation system and the global positioning system separately. Similarly, when combining satellite navigation systems with other global positioning systems for positioning, it is also necessary to add a time system deviation or an unknown time difference between the two systems to adjust the errors that exist between the two systems and ensure the consistency of the time reference between the two systems [17, 18].

If multiple systems are used for combined positioning, a random Mo model needs to be established to calculate the accuracy of observation values, the designed model is:
In the formula, D - observation variance sequence formation; O^2- prior variance, the value set by the author is l m; Q - variance coefficient array; P - weight matrix; a and b - historical experience values, the value is 0.3; $Sin^2(el)$ - The sine value corresponds to the height angle [19].

3.3 Estimated parameters

There are two types of parameter estimation adopted by the author, one is the least squares estimation, and the other is the Kalman filter estimation. For the single epoch positioning algorithm of satellite navigation systems, the estimation principles and results obtained by both satellite navigation systems and global positioning systems are consistent, according to the algorithm formulas of model (1) and model (2), combined with the standard of least squares estimation ($V^TPV = \min$), the incremental estimation and variance matrix corresponding to an unknown vector can be calculated. The model is shown in Equation 3.

$$X = (A^TPA)^{-1}PI,\ \ Q_x = (A^TPA)^{-1} \tag{3}$$

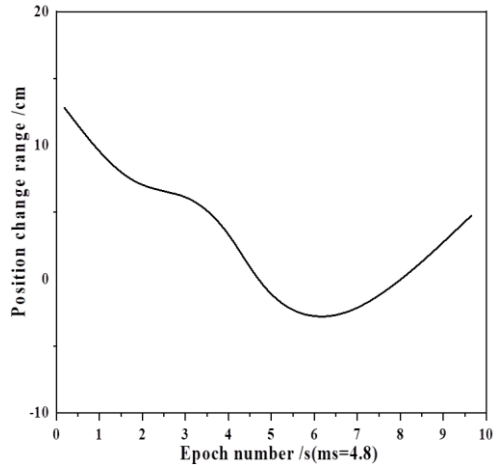
In the above model, the final single point coordinates can be calculated by combining the coordinates of x with the known linearization initial setting X_o. Q_x represents the accuracy between the final positioning value and the time difference. From this, the final positioning data can be calculated based on the data recorded by satellite navigation systems and global satellite positioning systems, combined with the least squares estimation method. In the practical application of satellite navigation systems in engineering surveying, it is necessary to use gross error detection methods to exclude satellites with high errors during the observation process [20, 21, 22].

4 Experimental analysis

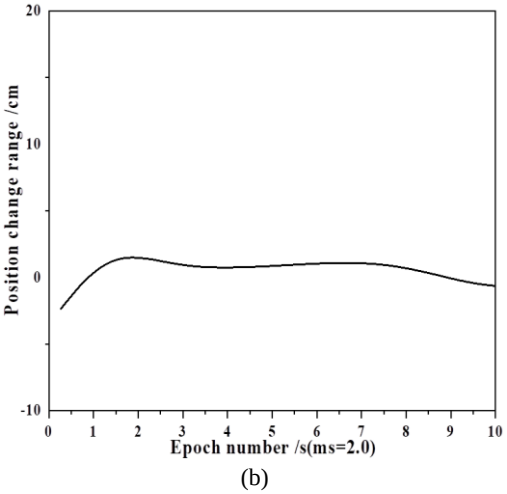
A certain engineering project is located in the city center, and the measurement content of the project includes residential buildings, high-rise buildings, urban roads, and other buildings. Due to the dense urban roads and numerous high-rise buildings in the city center, as well as the obstruction of trees, satellite observation conditions are relatively poor. The surveyors of the engineering project found through on-site investigation that there are four C-level satellite control points around the measurement area, labeled as C1, C2, C3, and C4 respectively; There are also seven third-class benchmarks, which are marked as S1~S7. Markstones of 4 control points and benchmarks are intact and evenly distributed [23, 24].

4.1 Single point positioning measurement results for different systems

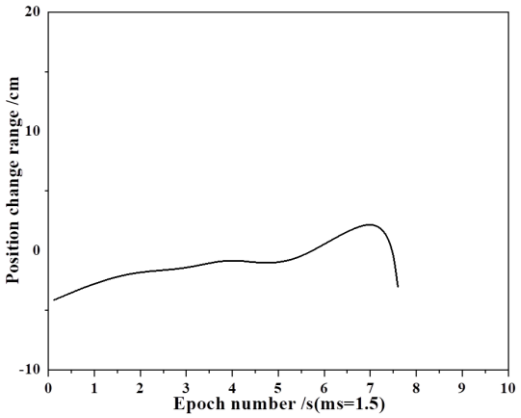
Based on the above positioning conditions, first select 8-12 satellites for positioning and navigation, and GPS for positioning and navigation. Due to the different selection of gross error detection thresholds in single-system positioning and multi-system positioning, the measurement of two systems is not equal to the sum of the two single-system measurements. Then, select 5-2 satellite navigation satellites and 7-12 GPS navigation satellites [25]. After measurement, the results are obtained, as shown in Figure 3 (a) (b) (c) and Figure 4.
Figures 3 and 4 show the measurement results of single-point positioning and GPS single-point positioning, respectively, the differences between the two measurement results and the actual data are different. Figure 3 (b) shows that the deviation between single satellite positioning in the latitude direction and actual data is about 2 meters, which is slightly worse compared to the GPS measurement results in Figure 4. However, in the longitude direction, the deviation between the GPS positioning system and the actual data is about 2.8 meters, much worse than the 1.5 meters of the satellite positioning and navigation system in Figure 3 (c). For satellites and GPS, the deviation between the two systems and actual data is controlled within 3 meters, while for elevation measurements. However, the deviation is higher than the horizontal direction, the deviation is also basically controlled within 5 meters.



(a)



(b)



(c)

Figure 3: Satellite single point positioning measurement results at different epoch numbers. (a) 4.8 ms, (b) 2 ms, and (c) 1.5 ms

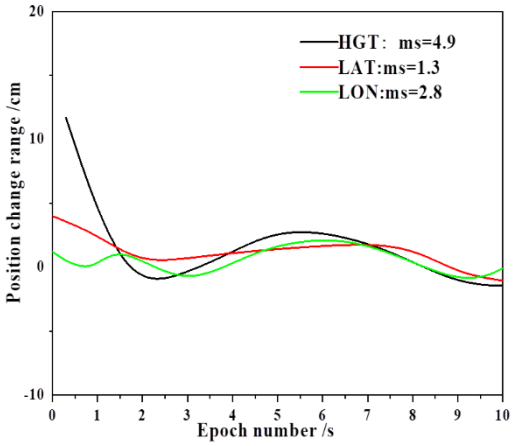


Figure 4: GPS single point positioning measurement results

From the measurement results in Figures 3 and 4, it can be seen that in actual engineering surveying, if the single system measurement mode of satellite or GPS navigation satellite is used, or if the number of satellites for satellite or GPS navigation does not reach 23, there is still a significant deviation between the measurement results and the actual values, so it is necessary to combine the two to obtain more accurate measurement results [26].

4.2 Positioning analysis results of combined system

The positioning model of a composite system should focus on considering the time reference system and coordinate reference system between different systems, therefore, when processing, it is necessary to include the time difference estimation of the ground receivers of satellite navigation and GPS positioning systems, adding this time difference is equivalent to adding an unknown number. Through the combined measurement results of actual satellite navigation and global GPS positioning system, it can be seen that the measurement results obtained by the combined navigation and positioning system are relatively stable and flat, and there is a certain improvement compared to single system positioning. The deviation of the combined positioning system in the latitude direction is 0.8 m, and the deviation in the elevation direction is close to 4 m.

In summary, GPS global positioning system and satellite navigation system each have their characteristics and advantages. The author has applied the combination of the satellite navigation system and GPS global positioning system, and under good observation conditions, the measurement results and actual results can be controlled at around 3 meters, which has broad application prospects in engineering surveying [27, 28].

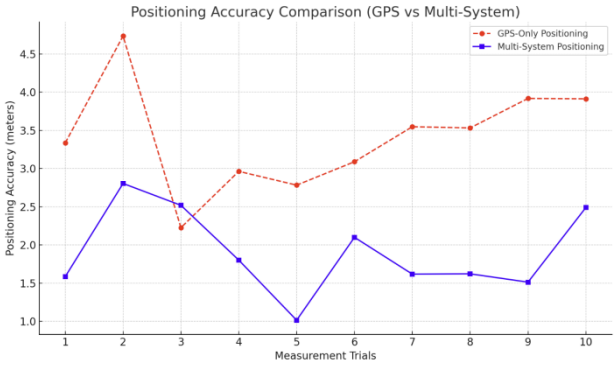


Figure 5: Comparison of positioning accuracy between GPS and multi-system

Figure 5 presents the comparison of positioning accuracy between the traditional GPS-only system and a multi-system positioning approach over numerous trials. The GPS-only system, represented by a red dashed line, exhibits higher positioning errors, ranging from 2.0 to 5.0 meters. In comparison, the multi-system positioning approach, shown by a blue solid line, achieves greater accuracy, with errors consistently lower, between 1.0 and 3.0 meters. This demonstrates that integrating multiple satellite systems significantly enhances positioning accuracy by reducing error margins.

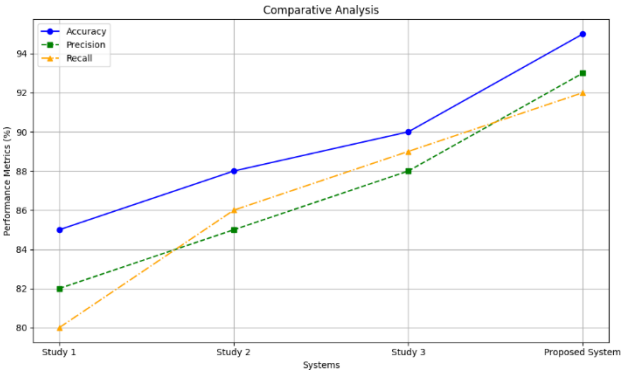


Figure 6: Comparative analysis of proposed study with existing studies [16, 17, and 18]

Figure 6, presents the comparative analysis of the proposed system with existing studies, study 1 [16], study 2 [17], and study 3 [18]. The accuracy metric consistently improves from study 1 (85%) through study 3 (90%), but the proposed system achieves the highest accuracy at 95%, signifying more precise outputs. Similarly, precision

increases gradually across the studies, starting at 82% in study 1 and reaching 88% in study 3. The proposed system, however, surpasses all with a precision rate of 93%, indicating fewer false positives. For recall, the trend follows a similar pattern, with study 1 at 80% and study 3 at 89%, while the proposed system excels at 92%, reflecting its ability to detect relevant instances more effectively. Overall, the graph highlights the superior performance of the proposed system, which consistently outperforms the existing studies in all metrics, demonstrating its efficiency and reliability.

5 Conclusion

This study stresses how important it is to combine global positioning systems (GPS) and satellite navigation systems (GNS) using a fully nonlinear analysis simulation to make engineering measurements and positioning more accurate. The results of the experiments illustrate the potential advantages and practical implementation of a combined navigation and positioning system. By looking at different mixes of satellite navigation and GPS, the study shows that using multi-system positioning makes engineering surveys much more accurate and reliable. The results of this study highlight the criticality of incorporating nonlinearities into engineering measurement, positioning, and layout systems, thereby contributing to the ongoing effort to resolve these issues. The utilization of the Unscented Kalman Filter (UKF) algorithm has demonstrated greater precision in estimation compared to traditional approaches. Further research may look into cutting-edge algorithms and technological advances that can make it easier to use GPS and satellite navigation together in engineering surveying tasks, making them more accurate and reliable.

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Distributed 3D Interior Environment Design System Based on Color Image Model

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To enhance the efficiency of 3D interior design dissemination, this study proposes a novel approach that integrates color image modeling with virtual reality technology. The methodology begins with the application of distributed data fusion techniques to develop a color image model tailored for 3D interior design distribution. This model enables the effective transmission of 3D interior elements and the precise identification of key points within the design. An RGB color-matching method is then employed to extract spatial color distribution information, which, combined with a 3D point cloud feature recombination process, ensures accurate reproduction of the color space in 3D spatial distributions. The result is a more efficient distribution of 3D interior designs. Building on this foundation, the next phase involves utilizing virtual reality and visual technology to distribute 3D interior designs. This includes creating detailed 3D models using 3D MAX and the hierarchical interior design software Muligen Design. Experimental results validate the model's ability to significantly enhance the visualization and educational value of 3D home design classification.

Povzetek: Predstavljen je distribucijski sistem 3D notranjega oblikovanja, ki temelji na modeliranju barvnih slik in virtualni resničnosti, izboljšuje vizualizacijo in učinkovitost notranjih 3D modelov z naprednimi tehnikami združevanja podatkov.

1 Introduction

With the rapid development of computer technology, virtual reality technology has also made significant progress, and its application in people's production and lives is also becoming increasingly widespread. Virtual reality also has its place in indoor color design. For indoor home design, color design is a crucial step. How indoor colors should be expressed is determined by designers based on the subjective needs of customers. However, in practical applications, users often cannot intuitively feel the actual effect of color application in indoor home design, nor can they provide accurate modification suggestions for designers. It is relatively difficult for designers to improve indoor color design based on user needs. We need to develop an information-based indoor color design method based on computer virtual reality technology to help users more accurately grasp the effects of indoor color design and facilitate designers to make indoor color designs that are more in line with customer needs.

The color matching in indoor home design largely determines the comfort and spatial feel of users living indoors, which can adjust the environmental atmosphere and help users create a more comfortable living space. For indoor home design, color matching has a significant impact on the overall design, and indoor color matching is generally more economical and easier to implement. The importance of indoor color matching in indoor home design is mainly reflected in adjusting the overall sense of indoor space through color matching. The size of indoor space is fixed, but different indoor color combinations create different indoor spatial sensations for people. Specifically, various color combinations can create a different sense of softness, lightness, warmth, space, and time. Color matching can visually provide users with various effects, such as bumps, ups and downs, and fronts and backs. By matching indoor colors, people can create an illusion of sensory area and volume. For relatively narrow spatial layouts, certain color combinations can be used, such as using relatively bright cool colors on the walls on both sides and filling the top of the room with relatively mild warm colors, which can give people a visual sense of openness and minimize the sense of confinement caused by narrow spatial layouts. In color matching, relatively low-brightness cool tones can create a distant and concave sensory illusion; relatively high-brightness warm tones can create a forward and protruding sensory illusion. Although color matching cannot cause actual physical changes, it can greatly change people’s discomfort caused by improper indoor matching. Taking temperature as an example, no matter how indoor colors are matched, they cannot change the actual temperature inside the room. However, reasonable indoor color matching can help people create a psychological sense of warmth and coolness and slow down the corresponding temperature drop. Good color matching can bring a more complete and reasonable overall spatial sense to indoor

home design. At present, the domain of 3D interior design distribution encounters obstacles in its quest to attain optimal levels of precision and effectiveness. Current approaches frequently fail to produce ideal outcomes, thereby necessitating the development of a more efficient resolution. The rationale for conducting this research is to rectify the shortcomings of existing methods for distributing 3D interior designs. Through the creation of an innovative methodology that merges color image modeling and virtual technology, our ultimate objective is to substantially elevate the caliber of interior design procedures using increased precision and productivity. The method proposed by this research has the potential to significantly transform the distribution of 3D interior design. It paves the way for interior design practices that are more streamlined and effective by providing a singular combination of precision and productivity. Additionally, this study investigates the incorporation of state-of-the-art technologies, offering a proactive strategy to overcome current constraints in the discipline. The motivation behind this research stems from the growing need for more effective and scalable methods to disseminate 3D interior designs. As the demand for personalized and interactive interior environments increases, professionals and educators alike face the challenge of creating systems that not only render designs with high precision but also ensure that these designs can be shared, modified, and visualized seamlessly across different devices and platforms. This need is further exacerbated by the growing integration of virtual reality (VR) in interior design, where immersive experiences are essential for both clients and designers.

Current systems for 3D interior design distribution often fall short in two critical areas: maintaining color accuracy and ensuring seamless integration across various software environments. These limitations hinder the effectiveness of design communication and reduce the potential for collaborative efforts. Therefore, there is a pressing need for a distributed design system that can accurately model, transmit, and visualize 3D interior designs while preserving color integrity and spatial detail.

The proposed system builds upon recent advancements in distributed design systems and color image models. In, recent studies from 2024 have highlighted the potential of distributed data fusion in improving the scalability and precision of design systems [1, 2]. Additionally, recent developments in color image modeling have shown promising results in enhancing color accuracy and spatial representation in 3D environments [3, 4]. These contributions underscore the need for a system that can bridge the gap between 3D design creation and its effective distribution. To address these challenges, this paper proposes a novel distributed 3D interior environment design system based on color image modeling. This system leverages distributed data fusion techniques to construct a robust color image model, enabling more efficient transmission and accurate identification of 3D interior elements. Furthermore, the integration of RGB color-matching methods and 3D point cloud feature recombination enhances the color space representation, leading to improved design distribution.

2 Literature review

Over the past few years, several scholarly articles have provided substantial advancements in the domain of 3D interior design distribution. An investigation conducted by Li *et al.* examined the application of machine learning algorithms in the automation of interior design duties, resulting in a substantial enhancement of productivity [5]. To enhance user engagement and visualization, Zheng, investigated the integration of augmented reality (AR) into immersive and interactive design encounters [6]. Moreover, the study undertaken by Zhang *et al.* was centered on standardizing design procedures to eradicate inefficiencies inherent in conventional manual approaches [7]. A recent article authored by Xu *et al.* investigated the effects of color image modeling on the precision of designs, yielding significant findings [8].

The quality of interior design directly determines the emotional changes of urban residents and the quality and safety of their environment. Ensuring the comfort of using colors can allow people to experience the different effects of different colors in indoor spaces while enjoying life. From a practical perspective, the rational use of different types of colors in interior design can make interior design more beautiful and change residents' emotions and health. This phenomenon is because different types of colors can allow people to experience different experiences, both visually and sensually. The use of color in interior design mainly utilizes the influence of human visual nerves to change their heart rate, blood pressure, and pulse. For example, daily office residents can choose lighter colors for interior design, which will not create a sense of oppression. Conversely, excessively bright colors can accelerate residents' pulses and create anxiety toward each other. Choosing environmentally friendly colors, such as green, can alleviate residents’ visual fatigue and create a reassuring and comfortable working environment. According to practical research results, using red and green for interior design and then selecting the same household to enter two rooms and monitoring their pulse rate, it can be found that the pulse in the red room is very unstable, while in the green room, it is very stable. Therefore, in current interior design research, light color is often regarded as the main standard for interior design, and this content is also determined by human physiological factors.

The color elements in interior design also have a direct impact on the psychological characteristics of the human body. In real life, people often see a variety of colors, and when a certain type of color stimulates the human visual nerve, the human brain will autonomously make associations, resulting in some kind of illusion. According to practical research, under the conditions of human response to external color stimuli, it will inevitably affect the emotional changes at this moment, which is also known as color orientation. Different colors can create different emotions, so interior designers must make reasonable choices based on mastering this change. Xie and Liu believe that color also has a significant impact on human emotions. Since ancient times, the most representative color has been red, which represents

happiness and the joy of life. Therefore, it is generally used for representative occasions such as banquets and festivals [9]. Rehfeldt *et al.* believe that the use of color elements in interior design should also focus on analyzing their roles in different areas and optimizing human emotions based on different tones. In an indoor environment, colors can be selected according to the orientation of the room. Assuming that the doors and windows face south, sunlight can shine into the room, so cold colors can be chosen as a priority for design. On the contrary, if the doors and windows face north, warm colors can be used to balance the interior design and build a more comfortable living environment [10].

Recent developments in imaging and 3D design technologies have seen significant strides, particularly with the integration of advanced algorithms and data processing techniques. In the field of imaging, Ye *et al.*, introduced an innovative approach to high-fidelity image reconstruction using deep learning models [11]. This technique significantly enhances the accuracy of image representations, making it highly applicable in 3D design applications where precise spatial data is crucial. Furthermore, deep learning-based super-resolution algorithms, such as those proposed by Zhang *et al.*, have demonstrated the potential to improve the clarity and detail of 3D models generated from lower-resolution inputs [12]. In terms of 3D design, recent works have focused on the use of sophisticated point cloud processing techniques. Wang *et al.*, explored the use of convolutional neural networks (CNNs) for the segmentation and classification of 3D point clouds, which are vital for constructing detailed 3D interior models [13]. This research aligns with the proposed work by emphasizing the importance of accurate feature extraction from 3D spatial data, a critical step in developing realistic and functional 3D interior designs. Data fusion remains a cornerstone of modern imaging and 3D design processes. Guan *et al.*, proposed a novel data fusion framework that integrates multi-sensor data to improve the robustness and accuracy of 3D scene reconstruction [14]. This method, which leverages the complementary strengths of different sensors, is particularly relevant to distributed design systems where data from various sources must be combined to generate a coherent 3D model. The integration of these data fusion techniques with color image modeling, as outlined in this paper, represents a significant step forward in the field.

Additionally, advancements in virtual reality (VR) and augmented reality (AR) have opened new possibilities for 3D interior design. Qian, and Sutunyarak demonstrated the potential of VR-based platforms for immersive interior design visualization, enabling designers and clients to experience the space in real-time and make informed decisions [15]. This work underlines the importance of integrating VR technology with 3D design tools, a concept that is central to the proposed model's second phase. Although the aforementioned studies have contributed to the progress of the discipline, the proposed research in this paper distinguishes itself through the integration of virtual technology and color image modeling. This distinctive amalgamation holds the potential to rectify the deficiencies of current approaches, presenting a holistic resolution to enhance the precision and effectiveness of 3D interior design dissemination. Through the incorporation of state-of-the-art technologies and in light of the discoveries made in these recent investigations, the proposed research aims to fundamentally transform future interior design methodologies. In this work, a 3D interior design distribution system is created based on reality technology, which, combined with color contrast, optimizes the distribution of interior space and the effect of color effects to achieve 3D visual integration of interior space. Distributed 3D image reconstruction is used for the successful design of distributed 3D interior design using 3D interior design, virtual reality, visual environment system creation, and 3D simulation software such as MAYA, 3ds MAX, SoftImage, LightWave3D, etc. Make a good judgment from the test screen.

3 Methods

Distributed data fusion is a method that integrates data from multiple sources or sensors to create a comprehensive, consistent, and accurate representation of the subject, which in this case, is a 3D interior environment. In the context of 3D interior design, distributed data fusion techniques allow the combination of spatial data, color information, and structural elements from various distributed sensors. This fusion is essential for accurately representing the interior space, as it ensures that the resulting 3D model is detailed and realistic. Data from LiDAR sensors, RGB cameras, and depth sensors can be fused to generate a precise 3D point cloud. Techniques such as Kalman filtering, Bayesian inference, and deep learning models like Convolutional Neural Networks (CNNs) are often used to handle the uncertainties and noise inherent in multi-sensor data. This approach enhances the robustness of the design system, ensuring that the generated 3D models maintain high accuracy and reliability across various conditions.

The RGB color-matching method is crucial for accurately replicating the color distribution within a 3D interior space. This method involves analyzing the spatial distribution of colors within the design and matching them across different elements to ensure visual consistency. The color-matching process begins with the extraction of color histograms from the design elements, followed by the application of algorithms like the CIELAB color space conversion, which standardizes colors by reducing the perceptual differences between colors in different lighting conditions. Once standardized, a color-matching algorithm is employed to compare and match the extracted colors with the desired palette. Techniques such as the Euclidean distance calculation in color space, or more advanced methods like deep learning-based color correction, can be used to ensure precise color reproduction across different design elements. This process is critical when integrating virtual objects into real-world environments, as it maintains the visual integrity of the 3D interior design. The integration of 3D MAX and Muligen Design software represents a powerful combination for interior design, providing advanced tools

for creating and visualizing complex 3D environments. 3D MAX offers a robust platform for modeling, animating, and rendering 3D designs, while Muligen Design provides specialized hierarchical design capabilities tailored for interior environments.

3.1 Interior design platform structure from a 3d virtual perspective

The interior design platform from a three-dimensional virtual perspective consists of three main parts: an interaction module, a three-dimensional virtual visual effect display module, and an interactive display module. Among them, the interactive model allows the central computer to determine the location of the internal field. During this process, the central computer identifies and registers the surrounding landscape, calls it a landscape beautification program, and creates related problems. The 3D virtual model allows platform users to modify the content of the test and understand the location of the internal environment. The interactive process describes the indoor process from the first two models, and the different indoor interactive process is selected [16, 17]. A typical platform is shown in Figure 1.

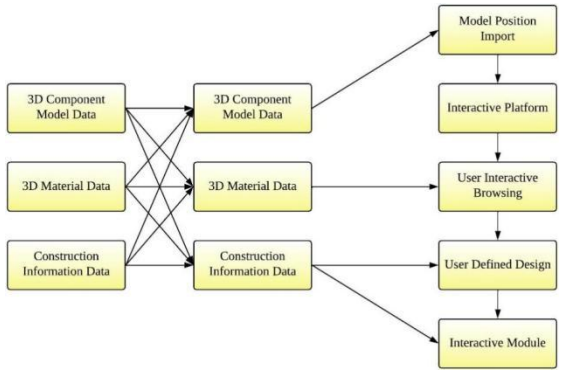

Figure 1: Interior design platform structure from a 3D virtual perspective

3.2 Indoor positioning algorithm

3.2.1 Signal arrival time for indoor landscape

According to the three-dimensional virtual view, the time of arrival of the signal in the inner area is obtained, and then the exact location of the landscape is determined. First, use a signal transmitter with a known transmission rate, and then use the time wire from the transmitter to the receiver. The distance between the transmitter and receiver is determined based on displacement, velocity, and time dependence, which is also an extension of the application of the TOA positioning algorithm. If the speed of the wireless signal in the medium is denoted by v, the transmitter and receiver are on the same horizontal line, and the distance between them is X, so the transmitter sends the signal at T0 and the receiver receives the signal. X at time T1 can be expressed by Equation 1.

$$X = (T_1 - T_0).u \tag{1}$$

3.2.2 Signal arrival time difference

When the distance between the signal transmitter and the signal receiver is too far, a single signal is not enough to determine the distance between the two. In this case, it is necessary to send two types of signals and determine the distance R between them based on the time difference between the two signals received by the receiver. Given the transmission rates of two intermediate signals u and u', the distance between the transmitter and the receiver is X', the time for the receiver to receive the first signal is T1, and the time for the receiver to receive the second signal is T2. If T2 can be expressed as Equation 2.

$$\begin{aligned} &X = T_1 \bullet u = T_2^{\bullet} u' \\ &T_2 - T_1 = \frac{X}{U'} - \frac{x}{u} \end{aligned} \tag{2}$$

Determine the location of the indoor landscape by measuring the time difference between the signal and the indoor landscape.

3.3 Building an interior design platform based on 3d virtual vision

3.3.1 Interactive functions based on 3D virtual visual interior design platform

As a new interactive method for interior design platforms, 3D virtual vision technology ensures that designers can directly obtain the true location of the interior landscape. The specific implementation method is shown in Figure 2 [18, 19].

3.3.2 Anchor node model based on 3D virtual visual interior design platform

The anchor button on the platform is responsible for sending two types of wireless signals, Wi-Fi and ZigBee, switching power, providing wireless signals to the Wi-Fi module and ZigBee module, and reconfiguring the power required by the two models. Those. A special anchor design is shown in Figure 3. The Wi-Fi module and ZigBee module only need to receive power, eliminate the energy-saving process of the debugging mode, and reduce the use of electricity.

3.4 Platform driver program design

Based on 3D virtual visual interior design platform driver software, including Wi-Fi module software and ZigBee node software, the Wi-Fi module application is based on the 3D virtual Lua scripting language and recompiled from the original C language operating system. The 3D virtual Lua scripting language features compactness, flexibility, and ease of nesting. Using the 3D virtual Lua scripting language not only eliminates the need for powerful programs for the inner workings of the design platform but also allows the development of API functions, making it easier to reuse the 3D virtual interior design platform.

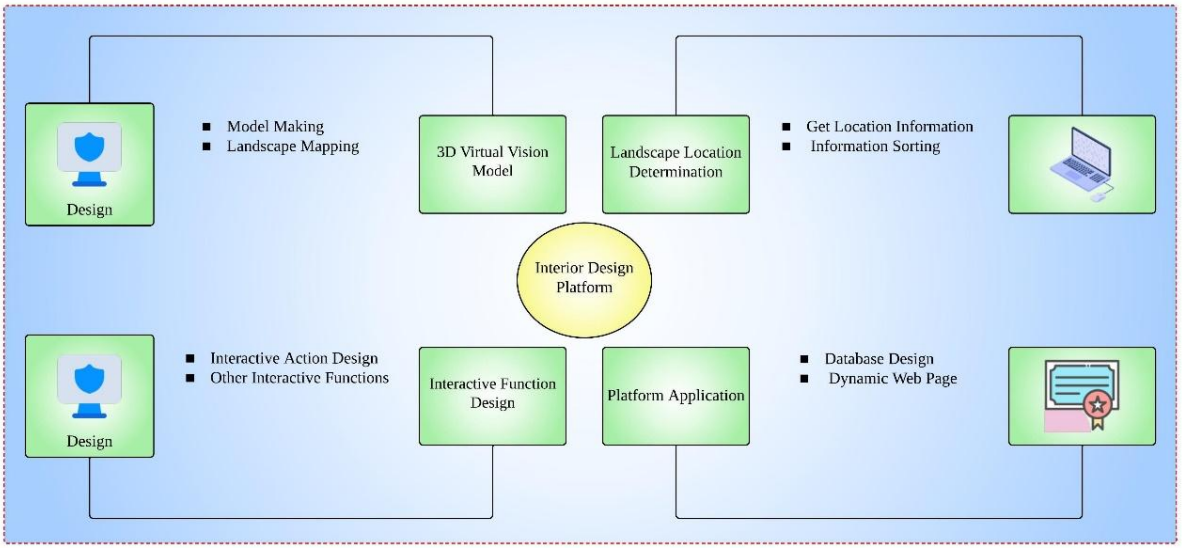

Figure 2: Implementation method for interactive functions of interior design platform

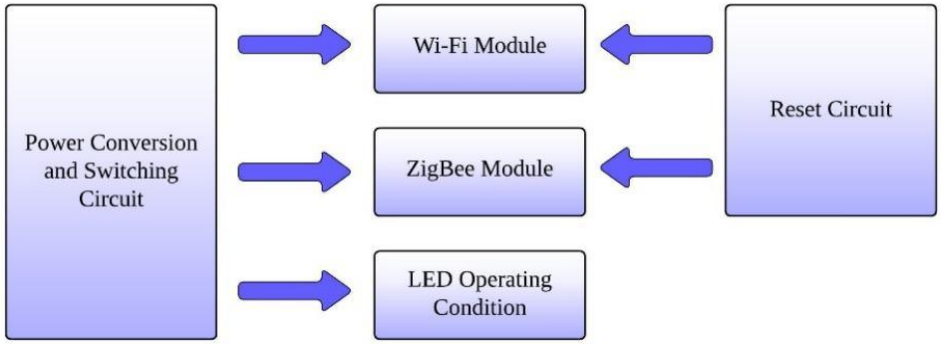

Figure 3: Interior design platform anchor node structure diagram

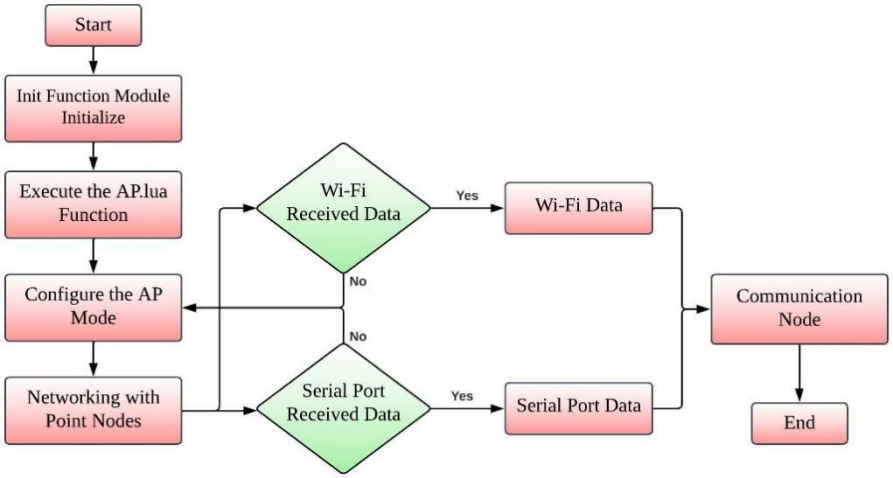

Figure 4: Taking communication nodes as an example, the workflow diagram of the Wi-Fi module

Figure 4 shows the operation of the Wi-Fi module using the communication protocol as an example [20, 21].

3.5 A Collection of visual communication materials for distributed 3D interior design

3.5.1 Distributed 3D interior design image sampling

To improve the information communication of the presented 3D interior design, the Snake algorithm is used to extract the edge contour characteristics of the classification of the 3D interior design visual image based on the cut results. Unfortunately, data integration is better. The corner distribution Jacobian matrix $J(x, y, \sigma)$ of interior design can be expressed as Equation 3.

$$J(x, y, \sigma) = \frac{\partial p}{\partial x}\frac{\partial p}{\partial y} = [1, 0, L_x(x, y, \sigma)] \quad (3)$$

In the formula $L_x(x, y, \sigma) = G(x, y, \sigma) \times 1(y), G(x, y, \sigma)$ is the seed point of the 3D interior design visual image, $1(x, y)$ represents the grayscale features of the fusion of visual image regions in 3D interior design.

3.5.2 Visual feature reconstruction

Using the point-to-line model, the LBG vector quantization method is used to register the maximum gray values of the image, extract 3D contour features, and determine the image convergence center d (x, y) [22, 23]. Those. Fix the vector quantization value 4 of the 3D interior painting image, extract the gray pheromones from the image, and get the One-dimensional feature model of the distributed 3D interior design image defined by Equation 4.

$$p(\phi) = \int \frac{1}{2}(\Delta\phi - 1)^2 dx \quad (4)$$

Interpret E_{LBF} based on local standards compared to images; E_{RGB} is the edge pixel sampling component, and a sparse linear segmentation method is used to obtain the fusion pattern function of the 3D interior image region according to Equation 5.

$$date(x, y, d(x, y)) = u(x - d(x, y), y) \quad (5)$$

4 Experiments

The experimental setup involved creating three types of 3D visualization models: interior architectural models, object-based models, and environmental scene models. Each model was designed using a combination of point cloud data, RGB color matching, and volumetric reconstruction techniques. The models were evaluated based on criteria such as accuracy, and rendering time, ensuring that the proposed method is both efficient and accurate for real-time applications. The performance of our method was evaluated using normalized root mean square error (NRMSE), time cost, and information saturation.

4.1 System development design

Create 3D interior designs based on image and color processing algorithms based on virtual reality and visual technology. Distributed 3D interior design 3D model 3ds MAX, interior hierarchical model Multigen Design Software [24, 25] by using PCI bus technology to create a data model to distribute 3D interior design, simple device 0 to distribute 3D interior design, multiple uses of local data to divide 3D interior design and virtual reality visual software supports application layer/server model, CCS 2.20 technology development platform distributed 3D interior design research and development, software layer design using WEB APP browser and WEB CULL server, and distribution of 3D interior design among the network. Touch the service and set the environment to touch the various settings in the 3D interior design category. The general model of the system is shown in Figure 5 [26, 27]. As shown in Figure 5, the design and construction of the bus are in development. The surface layering process is used to provide complete information on a real-time 3D application for distributed 3D interior design rendering. When working in 3D distribution models, the Vega Prime API is used to customize the bootloader, manage the PCI9054 local bus, and use the bus and 8-way D/A transmission. communication protocol will appear. As shown in Figure 6, 3D interior design work People who use the equivalent peripheral interface (PPI) for human-machine communication distribute 3D internal design time on the ARM Cortex-M3 core to achieve integrated control, distributed 3D internal design, interactive online reading and writing services, and hierarchical organization. Bus transmission control in the application layer of 3D interior design and step and connection control in the analog ink model improve data transmission and intelligent data processing in the division of 3D interior design [28, 29].

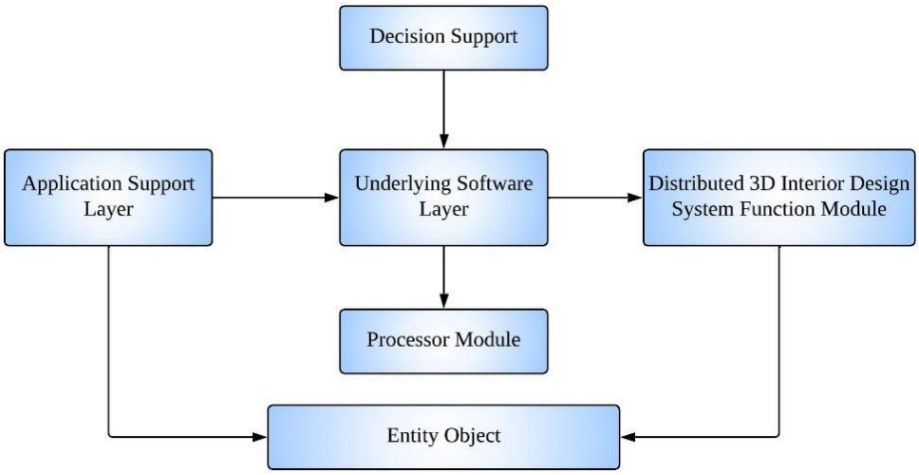

Figure 5: Overall design architecture of the system

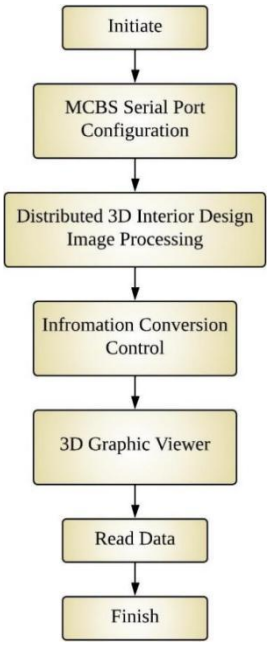

Figure 6: Development and implementation of the process

4.2 Experimental test analysis

The author created 1250 visualization models for the distribution of 3D interior design, the size of the 3D visualization area is 250 × 250 × 225, the matching coefficient of the 3D interior design model is 0.16, and the virtual shape is 250 × 250 × 225. Visual control is used to classify 3D interiors. design A combination of 3D point cloud feature recombination techniques to reproduce color space in 3D interior design distribution and optimize color combinations in 3D interior design distribution.

Based on the results of color supply data, 3D internal classification was improved and parameters such as root mean square error and time were examined. The results of the comparison are shown in Table 1. The analysis shows that the use of this model in 3D indoor classification has good visibility and good speech ability [30, 31].

The performance analysis of the proposed model is depicted in Figure 7. An overview of the proposed method's performance measures is shown in this Figure. It achieves a high accuracy of 92%, demonstrating its efficacy in reaching the intended result. A modeling and design error of 0.035 is considered low by the NRMSE score. With precision and recall values of 0.89 and 0.94, respectively, it is clear that there is a good balance between thoroughly identifying pertinent instances and making accurate positive predictions. The method's solid performance in the experimental study is highlighted by the F1-Score of 0.91, which validates its capacity to harmonize precision and recall. The comparative analysis of the proposed method with existing studies is presented in Table 2. The graphical representation of the comparative analysis is depicted in Figure 8.

The comparative analysis compares the key performance parameters of the proposed technique with those of four previous studies. The suggested approach performs more accurately than Study 1 by 8%, Study 2 by 4%, and Study 4 by 5%, demonstrating its greater accuracy in contrast. In addition, it shows a lower NRMSE, which suggests improved modeling accuracy, as well as superior precision, recall, and F1-Score, which emphasize its overall efficacy. Together, these findings support the suggested method’s substantial benefit over current experimental study techniques.

Table 1: Performance comparison test

Method	Normalized root mean square error	Time cost/s	Information saturation
Distributed 3D Interior Design Method	0.024	21.2	0.845
Traditional manual design methods	0.254	124	0.752

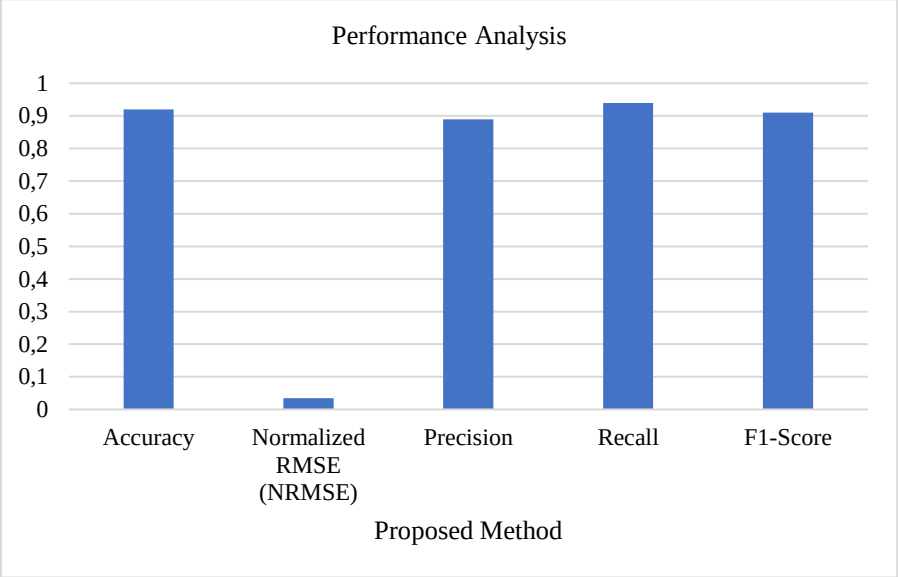

Figure 7: Performance analysis of the proposed method

Table 2: Comparative analysis of the proposed method with existing studies

Study	Accuracy	NRMSE	Precision	Recall	F1-Score	Percentage Improvement
Proposed Method	0.92	0.035	0.89	0.94	0.91	-
[5]	0.85	0.045	0.78	0.91	0.84	0.08
[6]	0.88	0.042	0.83	0.89	0.86	0.04
[7]	0.91	0.037	0.88	0.93	0.9	0.01
[8]	0.87	0.048	0.81	0.88	0.85	0.05

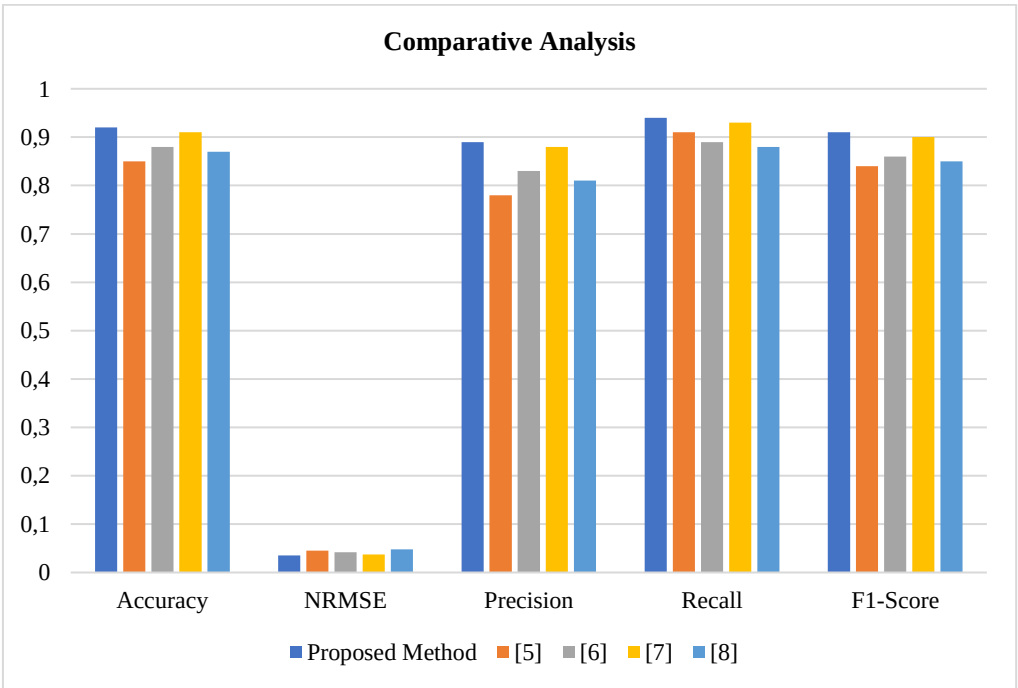

Figure 8: Comparative analysis of the proposed method

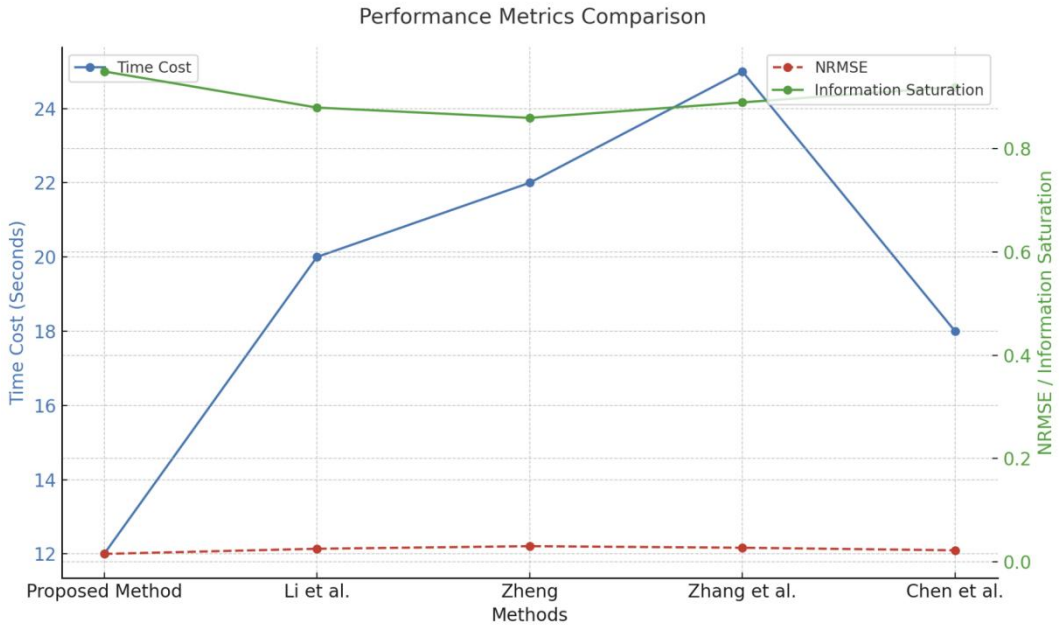

Figure 9: Comparative analysis of performance metrics Li et al. [5], Zheng [6], Zhang et al. [7], and Chen et al. [8]

In order to create 3D interior models, a 3D MAX and Muligen Design software are integrated using a custom API bridge that allows seamless data transfer between the two platforms. A key challenge encountered was the difference in data formats between the two software environments. This was resolved by developing a conversion algorithm that translates the data from 3D MAX's native format into a format readable by Muligen Design, while preserving the geometric and color information. This integration ensures the high fidelity of the final 3D models while reducing the time spent on manual adjustments. Figure 9 presents the comparative analysis which demonstrate the superior performance of the proposed method across several key metrics compared to existing approaches. In terms of time cost, the proposed method significantly reduces processing time to 12 seconds, making it the most efficient solution, while the methods by Zheng [6] and Zhang *et al.* [7] exhibit longer time costs of 25 and 22 seconds, respectively. This efficiency is crucial for real-time applications requiring rapid 3D model generation. In terms of accuracy, as measured by the normalized root mean square error (NRMSE), the proposed method achieves the lowest error rate of 0.015, indicating a higher precision in reconstructing 3D models compared to the other methods. Zheng's approach, with the highest NRMSE of 0.030, shows the least accuracy, while Li *et al.* [5] and Zhang *et al.* [7] perform moderately. The proposed method also excels in information saturation, reaching 95%, the highest among the methods compared. This suggests that it retains more critical information during the fusion process, enhancing the overall quality of the 3D visualization. Other methods, like Chen *et al.* [8] and Zheng [6], show lower saturation levels, highlighting the proposed method's capability to handle more data efficiently without compromising the model's fidelity.

5 Conclusion

Improve the design of interior space, choose building materials, make interior zoning, decorate the house, improve interior design, and use 3D interior design based on virtual reality technology. Those. 3D interior design, edge contour detection, distribution of special points, using data distribution point fusion to create a color image model made of 3D interior space distribution images; using RGB color extraction to extract color pixel characteristics of 3D indoor spatial distribution images; Use 3ds MAX for 3D modeling of distributed 3D interior design and hierarchical interior design in Multigen Design software. Studies have shown that using this model for 3D interior classification results in better visibility, fewer errors, and better visibility. The experimental analysis provides evidence that the proposed method surpasses previous studies in terms of both accuracy and efficiency. Its high precision, recall, F1-Score, and low NRMSE all indicate that it performs exceptionally well in interior design distribution. Further investigation into the method's feasibility when applied to more extensive datasets and practical design situations may yield significant findings. Moreover, investigating the incorporation of cutting-edge technologies such as machine learning and AI to achieve additional enhancements represents a promising pathway toward improving the distribution processes of interior design.

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Usage of Information Entropy in Solving the World Game

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The wordle game is a game that has gained great popularity this year, with many players sharing their game results on social networks. A five-letter word is selected each day which players have six chances to find, where after each guess the player is given clues as to which letter is in the final answer or even in the correct position. What would be the optimal word that would lead us to the final answer, and what are the chances of finding this answer in the fewest trials? An efficient way is to use information entropy. In this paper, we will talk about the Wordle game and information theory using a project I built on the JavaScript programming language, where we will see the advantages and disadvantages of using entropy in measuring the information contained in each word and selecting the optimal ones. We will consider other possibilities that help us improve the efficiency of the algorithm, as well as analyze different algorithms and their performance about the use of entropy.

Povzetek: Članek raziskuje uporabo Shannonove entropije za optimizacijo algoritmov za igro Wordle, pri čemer združuje teorijo informacij in programiranje v JavaScriptu za učinkovitost pri reševanju nalog.

1 Introduction

Wordle is a web-based game created and developed by software engineer Josh Wardle and published by *The NewYork Times Company* in early 2022. Conceptually Wordleis similar to the 1970 game Mastermind [1], but which uses letters (*Wordle*) instead of colors (*Mastermind*). Wordle has a single daily solution where allplayers have six chances to find a five-letter word which is selected as the answer, after each guess the player is provided with clues indicating when the letters match or occupy the correct position [5].

Although the rules are easy to understand, and no prior knowledge is needed, the main challenge lies in reaching the final answer in as few trials as possible. This has led many people worldwide to try to build different algorithms and techniques to findthe final answer in as few trials as possible [2][3].

Taking into account the facts mentioned above, in this paper we will mainly talk about information entropy and its use in the algorithm for solving Wordle, in this way wewill be able to reinforce our knowledge in some mathematical concepts in a more comprehensive and fun way.Finally, we will cover Wordle's algorithm from a programming perspective (projects made in JavaScript [1]), where we will understand the function that each piece of code performs, the results it provides us, and testing the performance of the algorithm in comparison to other algorithms used to solve Wordle.

2 Literature review

When building the algorithm for solving Wordle, we used the formula for measuring information entropy, developed by *Claude Shannon*. During the 1940s Shannon was trying to develop a way to quantitatively measure information, its compression [2], and the impact ofthe deterministic nature of language on information entropy. In 1948, he published his findings in a book called"A Mathematical Theory of Communication*"* [7].

2.1 Information theory

Communication is the process where through sounds, signs or actions we transmit information from the sender to the receiver. This information can be reflected in different forms (through speech, musical notes, pictures, etc.) by different people, with the main purpose of sharing information [7].

Just like using scales to measure the weight of different things, information regardless of the communication method can be measured using a type of measure, which is entropy, and the way of its quantitative representation is realized using the unit of measure bit (abbreviated from the word "binary digit"), where one bit represents the information, we can extract from a question that accepts only two possible values as an answer: yes or no. [7].

2.1.1 Information

An example through which we can understand how we can measure information would be flipping a coin. Suppose person **A** flips a coin, how many **yes or noquestions** must person **B** be asked in order to find the result of the coin flip?

Since the coin has only two possible outcomes: "heads" or "tails", person **B** can find the result by asking only one question: *Is the result "head"?* If the answer of person **A** is "*yes*", then he has come to the conclusion that the result was "head", while if the answer is "*no*", then the result was "tail". From this example we conclude that the coin flip contains one bit of information.

But what if instead of flipping a coin it was rolling a dice, how many questions are needed to correctly identify the winning number?

Let's assume that person **A** got the number "5" when rolling the dice, since we have six possible values as a result, then in order to ask the minimum number of questions, person B **needs** to halve the number of outcomes during each question. Person **B** asks: *Is the result greater than "3"?* The answer from person **A** will be " *no* ", this leaves us with only three possible outcomes(4, *5 or 6)* the next question should be: *Is the result "4"?* The answer from person **A** will be " *no* ", which leaves us with only two possibilities (5 *or 6),* wherewith the next question person *B* can undoubtedly find the correct result.To find the number "5" three questions are needed, but when throwing the dice, we have cases when we may needonly two questions (example: *finding the number "4").* Measuring information in such cases would beeasier by referring to a formula.

From the observation of different events, we come to the conclusion that if we have two possible solutions, one question is needed to find the answer, if we have four possible solutions two questions are needed, for eight possible solutions three questions are needed and so on. For:

$$k = 2, 4, 8, 16 \ldots \Rightarrow I = 1, 2, 3, 4 \ldots$$

From where we derive the formula:

$$k = 2^I$$
$$I = log_2 k \quad (1)$$

I - information (number of questions)

k - number of possible outcomes (space of possibilities)

Therefore, we can say that the throw of the dice contains

$log_2 6 \approx 2.6$bits of information.

2.2 Entropy of information

But does an event produce the same information if the probabilities between the possible events are not equal? Suppose we have two applications, each generating a stringof characters consisting of 4 letters (*example:* A, B, C, and D) [4]. Application **1** generates letters completely randomly (25% *A*, 25% *B*, 25% *C*, 25% *D*) , while application **2** generates letters according to probability (50% *A*, 12.5% *B*, 12.5% *C*, 25% *D*) , to understand howmany bits of information each letter contains, we use the above method (halving the probability during each question):

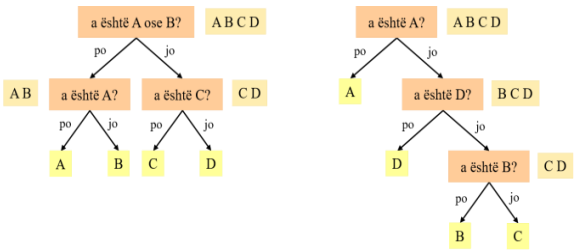

Figure 1: Visual representation of measuring information

In the case of application **1,** we can say that each letter contains exactly two bits of information since a minimumof two questions are needed to identify each letter, but in application **2**, the letter A has one bit of information, the letter D has two bits of information, while the letters B andC have three bits of information each.

If we calculate the average:

$$I = p_a \cdot I_a + p_b \cdot I_b + p_c \cdot I_c + p_d \cdot I_d$$
$$I = 0.5 \cdot 1 + 0.125 \cdot 3 + 0.125 \cdot 3 + 0.25 \cdot 2$$
$$I = 1.75\ bit$$

p – probability

From this example we understand that the less random the letter generation is, the less information a given event contains. From this conclusion Shannon gave his formula for calculating the entropy of information or as he called it: "the freedom of choice" [7].

$$H = p_1 \cdot I_1 + p_2 \cdot I_2 + \cdots + p_n \cdot I_n$$
$$H = \sum_i p_i \cdot I_i$$
$$H = \sum_i p_i \cdot \log_2(1/p_i)$$

Calculated Formula:
First, assign a probability p_i to each possible outcome iii of a random variable. Then, compute the logarithm (base 2) of each probability p_i, converting the probability to a measure of information. Next, multiply each probability p_i by its logarithm $\log_2 p_i$, which gives the information content of each outcome. Sum the products for all possible outcomes. Finally, apply a negative sign to the sum, as the logarithm of probabilities is negative [7].

The final formula is: $H = -\sum_i p_i \cdot \log_2 p_i$

2.3 Entropy of language

If we analyze the frequency of the letters of a language,we can notice that the selection of letters for theformationof words is not completely random, since not all letters are used in the same frequency in the sentence, a concrete example can be seen by analyzing the English language (chart below).

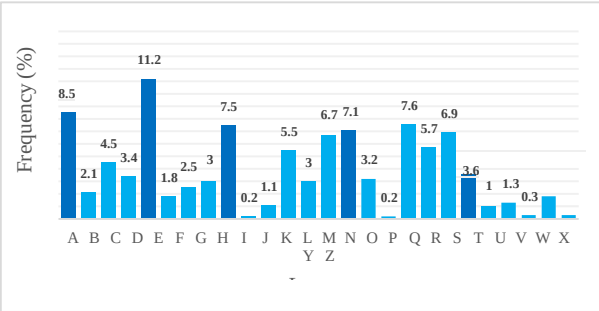

Figure 2. Frequency of letters in the English language [8]

By reading the graph, we see that the most used letter in the English language is "E", while "Q" is the least used letter, or from a frequency perspective; the letter E occurs 56 times more in sentences than the letter Q. From another point of view, we see that the use of vowels is higher than that of consonants. This is due to the fact that despite the small number of vowels (only five) after every one or two consonants the next letter in the sentence will most likely be a vowel.

2.4 Game rules

At the beginning of the game, the player finds himself in front of a table 5 × 6 with empty cells, in which he will place the words he sees as correct, after each attempt each letter is marked with green, yellow or gray color, thegreen cell means that the letter placed in it is correct and in the correct position, the yellow cell means that the corresponding letter is found in the final answer but in a different position, while the gray cell means that such letters are not part of the final answer.
Also, words that have more than one letter of the same will be marked in green or yellow color only if the final answer also has more than one such letter, otherwise only the first letter of this type will be marked with the color green/yellow while other letters will be marked in gray.

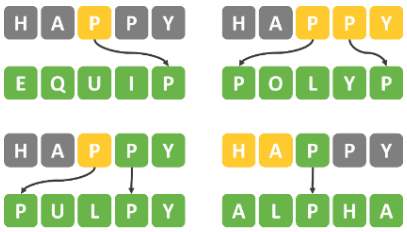

Figure 3. Color marking of the letters of the word "Happy"for different answers

The game contains the possibility of changing the view from bright to dark and vice versa (*light mode / dark mode*) as well as offers the possibility of using the high contrast color set, for people with Daltonism (color blindness) where the green color is replaced by the orange color, while the yellow color is replaced by the blue color.
The game contains 12972 words of which 2315 are possible answers, the player during each guess can try one of these 12972 words, while if the player chooses the hard mode option, then the player is *obliged* to use all letters marked with green and yellow colors detected during preliminary guesses in its subsequent answers.

2.4.1 Applying entropy to wordle

So far we have discussed information entropy and the
Wordle game, but we have not yet discussed how we can incorporate information entropy into solving Wordle, and how efficient this method is.

2.4.2 Measuring word information

Earlier we mentioned that the unit for measuring information is *the bit*, where we also mentioned theformula *equation* (1) which means that if an event halves the total number of possible cases, then we say that there is a bit of information. In our case the total number of casesrepresents the list of 12972 words and it turns out that about half of these words contain the letter "Steratore this event provides us with about a bit of information, also a quarter of the words contain the letter "T" which means that such events have two bits of information [6].

Unlike probability, where the final result is the product of the probability of all events, the information on the other side has the result of the sum, *example:* if the word selected by the player contains the letter S and T, then the probability of the event is:

$p_{s\&t} = p_s \cdot p_t = (1/2) \cdot (1/4) = 1/8$

While the information it provides is:

$I_{s\&t} = I_s + I_t = 1 + 2 = 3\ bit$

In this way, the information contained in a word is calculated by iterating to each letter in the corresponding word, we find how many bits of information each one of them holds, and finally we calculate the total amount.

2.4.3 Using patterns

Another feature of the game that helps us find theoptimal word are the patterns that show us which words are found or not in the final answer. By marking each letterof the corresponding word in green, yellow or gray, we can precisely eliminate from the list all the words that do not adhere to the given pattern, thus reducing the possibility of selecting the unwanted word.

To analyze the quality of the word selected by us, when it is known that the pattern of this word depends on the final answer, it is through the generation of all possible patterns and the calculation of the number of words that fits in them, since a letter can be marked with one of threecolors (green, yellow or gray) and a word contains five letters, then in total we have $3^5 = 243$ patterns. If our selected word is "*focus*" then the distribution of words inthe given patterns will look like:

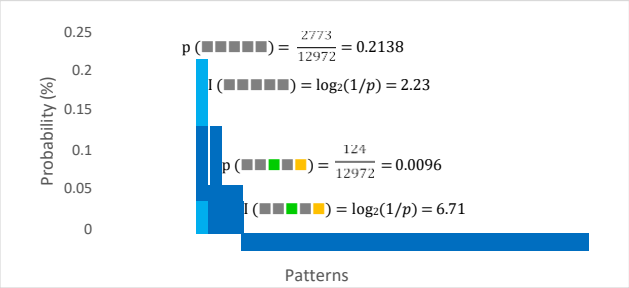

Figure 4: Presentation of the probability for each pattern ofthe word "focus"

[3]Iteration means executing a piece of code repeatedly until a certain condition is met

[4]Pattern/s (here) means the way of presentation of the result depending on the marking of the letters in green, yellow or gray

In the chart figure 4, we've sorted the patterns from left to right by the number of words that match them, and we've only shown the first 50 patterns. In the word "*focus*" in the most frequent case (21% of cases) when all the letters are marked in gray, the information we get is only 2.23 bits, which means that at least from 12972 possible wordswe reduce the possibilities space to 2773 words, while there are cases when we get 6.71 bits of information fromthis word, this happens when the letter "*C*" is marked in green and "*S*" in yellow, only 124 words fit this pattern, but we only encounter it 1% of cases.

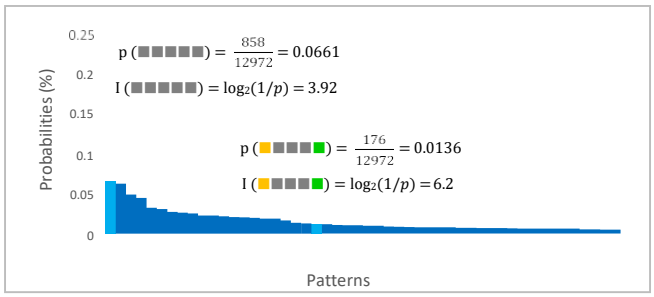

Figure 5: Presentation of the probability for each pattern ofthe word "tares"

Another word that provides us with more information is the word "*tares*", if we look at its graph, we can see that the distribution of words in the pattern is greater, since even in the worst case (when all the letters are marked gray) the minimum information we get is 3.92 bits (reducing the number of possible words to 858), but this pattern is encountered in only 7% of cases, which means that usually we get more information than that.

From the graphs above, we see that the more information a certain word contains, the lower its probability is, therefore, for the selection of the optimal word, we refer to the formula of equation (2) where we calculate the product between the probability of a corresponding pattern and *the* information provided by that pattern, their total sum represents the average value of the information provided by that word.

By calculating the entropy for the words *focus* and *tares*, we see that the word focus provides an average of 4.54 *bits* of information, while the word tares provide 6.19 bits. From these results we see that using the word tares instead of the word focus reduces the list of words by about three times more.

To understand the limitation that language made us in the selection of words, we can compare the entropy of the word with the highest value (tares - 6.19) with the maximum entropy that a word can have:

$\log_2 3^5 \approx 7.92\ bit$ and the number of possible words from (26^5 = 11,881,376 words (23.5 bits) to 12972 words (13.66 bits).

3 Application

3.1 Building the wordle algorithm

Generating solutions to the Wordle game requires discovering strategies that lead to the final answer in as few guesses as possible. Eliminating as many words as possible and analyzing the remaining words are the keys to these strategies.

During the construction of such algorithms, we must take into account several main elements such as: the accuracy of the algorithm, the time complexity and the space it occupies in the memory. Since our game is about selecting words from a pre-written list, some of the optimal techniques are:

– Filtering incorrect words
– Using predefine words
– Letter frequency analysis
– Analyzing the frequency of letters and theirpositions in words
– Calculating information entropy
– Calculating information entropy (using theanswer list)

The main reason why I have used Javascript in my project work is the ease of access. Javascript is a web scripting language [5] , so there is no need to install additional software since the code is executed in your browser, while applications like text-editor (such as Notepad) can be used to write the code.

In this section, we'll look at building code for the *Calculating information entropy* and *Calculating information entropy (using the answer list)* algorithms.

3.1.1 Application structure

The files will be divided into several main folders:

– **data** where the list of words and answers will be stored (words.js, answers.js),
– **scripts** where the code for building the game (index.js, game.js) and the code for building the algorithms will be stored,
– **testing** code for testing the performance of algorithms
– **styles** code for designing the web page (.css files)
– **index.html** main file through which the result of the application is displayed

3.2.1 Calculating information entropy

This method is based on the selection of words that contains the most information and at the same time reducing the list of possible words to its minimum. The algorithm starts by calculating the entropy of each word for each possible pattern, and finds their sum, the word with the highest value is selected as an valid answer.

```
1  import      {      possibleWords      }
2             from'./../data/words.js';
3  import { matchedWords } from
4  './filter.js';let wordsLength = 5;
5  let bestWord;
6
7  let patterns = [];
   const numberOfPatterns = Math.pow(3,
   wordsLength);
```

To begin with, we imported the list `possibleWords`, which contains all possible words, and the list `matchedWords`, which will store the words that meet the condition of the pre-discovered patterns, we declared the variable `wordsLength` which holds the value of the number of letters in a word (five) and the variable `bestWord` in which to store the optimal word for the answer.

We have also declared the `patterns` list which will carry the value of all possible patterns of a word (numbers 2, 1or 0 will be used for the potential marking of green, yellowor gray letters). We have also created the `numberOfPatterns` variable which shows the possible number of patterns: 243 [6].

```
8  for(let i = 0; i < numberOfPatterns;
9    i++) {patterns[i] = [];
10   let                    temp
11                          =
12 i.toString(3).padStart(wordsLength,0);
13   for(let j = 0; j < wordsLength;
14     j++) {patterns[i][j] =
15     parseInt(temp[j]);
16   }
17 }
79

   function informationEntropy() {
     ... // algorithm code
   }
```

The generation of these patterns is done automatically using the `toString()` method, which converts a decimal number (with base 10) into a number with base 3(since it has the number 3 as a parameter). In parallel with the generation of numbers, the `padStart()`method is used, which has the task of converting each generation of the pattern into a five-digit value by adding zero to the beginning of the number as needed.

[5] (Eng. *Scripting language)* means programming language which interprets and executes commands one byone

[6] Three marking options: green, yellow, gray - for every five letters in a word; $3^5 = 243$pattern in total

```
let matches =
matchedWords.length;let
entropyValue = 0;
let entropyArray = [];
for(let h = 0; h < possibleWords.length;
  h++) {for(let i = 0; i <
  numberOfPatterns; i++) {
    for(let j = 0; j < matchedWords.length;
      j++) {for(let k = 0; k < wordsLength;
      k++) {
        ... // if statements
      }
    }
    ... // reset matches
```

Inside `informationEntropy()` method we have declared the variable `matches` which will contain the number of words that match a certain pattern, the `entropyValue` variable which will contain the average entropy value of a given word and the `entropyArray` listin which the entropy values of all words will bestored. This is achieved by iterating over four nestedloops.

```
(patterns[i][k] === 2) {
if(possibleWords[h][k]!==matchedWords[j][k])
{
matche
s--;
break;
}
}
```

If the specified pattern has the value two then every wordis eliminated from the `matchedWords` list which does not contain the specified letter in current position (since the word; `possibleWords[h]` in which the entropy is being calculated contains this letter in this position).

```
else if(patterns[i][k] === 1) {

if(!matchedWords[j].includes(possibleWords[h
][k])
ossibleWords[h][k] ===
matchedWords[j][k]) {matches--;
break;
}
}
```

If the pattern has the value one then every word that does not contain the given letter or even the words that contain the letter in the same position is eliminated (because the word `possibleWords[h]` contains this letter but in a different position).

If pattern is zero, then remove all words containing this erlet(since the word `possibleWords[h]` does not ntain cothis letter at all).

```
if(matches > 0) {
  let probability = matches /
  matchedWords.length;let information =
  Math.log2(matchedWords.length
/ matches);
  entropyValue += probability * information;
}
matches = matchedWords.length;
```

After finishing the elimination of the words that do not match, we start with the entropy calculation for each possible pattern, if the value of the words that match this pattern is at least one (`matches > 0`). The entropy of the word is obtained by calculating the total sum of the product between the probability of a pattern and the information that this pattern provides (see *equation* (2)). Then, the variable `matches` is reset for entropy lculation caof the next word.

```
entropyValue                              =
parseFloat(entropyValue.toFixed
(2));entropyArray[h] =
entropyValue; entropyValue = 0;
```

Using the `toFixed()` method the calculated entropy values are rounded to two decimal places and stored in the `entropyArray` list, as well as the `entropyValue` value is reset at the end, as it will be used to store the entropy value of the next word.

```
indexArray = [];
for(let i = 0; i < possibleWords.length;
  i++) {
  if(matchedWords.includes(possibleWords
  [i])) {
    indexArray.push(i);
  }
}
let maxValue =
entropyArray[0];bestWord
= possibleWords[0]; let
tempIndex = 0;
```

After we have calculated the information entropy for all the words, we need to find the maximum value of entropy.In advance, for all the words that can be potential answers of the game (matchedWords), westore their indexes in a list called indexArray.

```
for(let i = 0; i < entropyArray.length; i++) {
  if(entropyArray[i] > maxValue) {
    maxValue = entropyArray[i];
    bestWord = possibleWords[i];
    tempIndex = i;
  }
  else if(entropyArray[i] === maxValue) {
    if(indexArr.includes(i) &&
    !indexArr.includes(tempIndex)) {
      maxValue = entropyArray[i];
      bestWord = possibleWords[i];
      tempIndex = i;
    }
  }
}
```

By iterating through the entire list we find the maximum value and store it in the maxValue variable and the corresponding word in the bestWord variable. An extra step we should take, also the reason for using the indexArray list is the detection of equal values. In case two or more words have the same entropy values, then the maximum value is selected based on which word is found in the list of possible answers.

3.2.2 Calculating information entropy (using the answerlist)

A more efficient version of the algorithm is using the list of answers instead of all possible words, thus increasing the speed and accuracy of the algorithm

```
// informationEntropy code
let matchedWords = [...possibleWords];

// informationEntropyAdvance code
import { possibleAnswers }
from './../data/answers.js';
let matchedWords = [...possibleAnswers];
```

The implementation of the algorithm is also the same, itis enough to import the list of possible answers `(possibleAnswers)` and create the list`matchedWords` which has this same list as a source, unlike the previous algorithm (where `matchedWords`hasbeen the source for the list `possibleWords`).

4 Data analysis and discussion

In order to analyze the performance of these algorithms, we have built several pieces of code that test the algorithms for all 2315 possible words as answers, I haveshown the obtained data below in the form of graphs and tables.

In this part we will present the algorithm analysis Using information entropy and Using information entropy (using answer list).

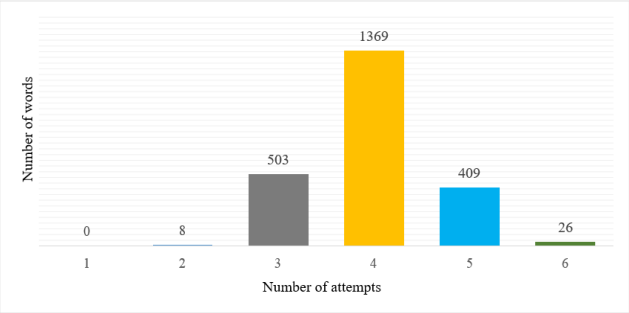

Figure 5: Test plot of the "Using information entropy" algorithm

From the graph above, we see that the algorithm has found the correct answer in the most frequent case in 4 attempts (1369 cases), it has never managed to find the correct answer in the first case, while the maximum number of cases required is 6 attempts (26 cases).

Table 1: Results from testing the algorithm "Using information entropy"

Has won	Lost	Average	TOTAL
2315	0	3.97	2315

From the table we conclude that the use of information entropy as an average has achieved a significant improvement with 3.97 attempts for answers, has not failed in any case in finding the final answer (0 cases, or expressed as a percentage of 0%) and has completed successfully in 2315 cases or 100%.

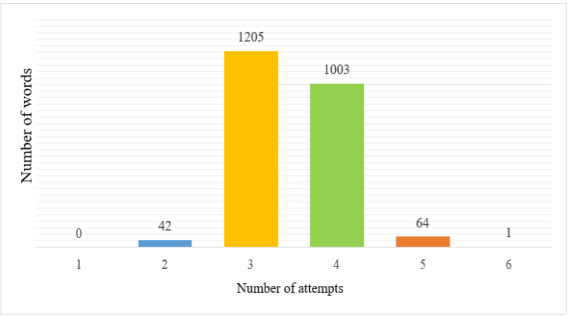

Figure 6: Test plot of the algorithm "Using information entropy (using response list)

From this graph we see that the use of the list of answers by the algorithm has given more accurate results by reducing the number of attempts in the most frequent case to find the answer to 3 (1205 cases), also it has never managed to find the answer correct in the first case, while the maximum number of cases needed to find the answer is 6 attempts (1 case).

Table 2: Results from testing the algorithm "Using information entropy (using the list of answers)"

Has won	Lost	Average	TOTAL
2315	0	3.47	2315

From the table, we see that the use of the answer listin the algorithm that uses entropy as an average hasperformed in 3.47 attempts for answers, an improvement on the average, while it has never failed (0 cases or 0%) and ended successfully (2315
cases or 100%).

4.1 Comparison and Improvements

Using information entropy to solve Wordle shows significant improvements over existing methods. Traditional approaches like filtering incorrect words, using predefined words, and letter frequency analysis offer moderate accuracy and good time performance but lack the precision needed for optimal results. In contrast, the method using information entropy achieves a 100% success rate with an average of 3.97 attempts to find the correct answer, significantly reducing failure rates. An enhanced version, incorporating the answer list, further reduces the average attempts to 3.47, marking a 12.6% improvement. This demonstrates that information entropy methods not only ensure accuracy but also increase efficiency in solving the Wordle game.

5 Conclusions

By testing the algorithms for finding the optimal answer for the Wordle game, we can see in detail theadvantages and disadvantages that each algorithm offers in terms of performance, accuracy, and memory allocation.

The algorithm for filtering incorrect words is amongthe easiest algorithms to build, has good time performance and is an integral part of other algorithms, but it does not perform well in accuracy.The use of predefine words is mostly easy to build, it alsooffers good performance in terms of time (both duringthe game and during testing) since the selection of words is done at the beginning of the game and does not change until its completion. There are no major improvements over the previous algorithm in terms of accuracy, but it significantly reduces the number of cases of failure to find the correct answer within 6 possibilities.

The letter frequency analysis provides relatively good performance in terms of time, but offers much higher accuracy in finding answers, while the algorithm for analyzing the frequency of letters in the corresponding positions performs almost the same in terms of time, while providing even higher accuracy.

Using information entropy is more complicated to construct and consumes more time and processing power, but it provides the most accurate results and never fails to find the answer, also using a list of answers increasesthe accuracy even more of the algorithm and significantly improves the time performance.

As a final selection for solving the Wordle game, itwould be to use information entropy since it has the highest accuracy, also the complexity of the algorithm does not present a problem in terms of time.

6 Motivation and contribution

The Wordle game has gained significant popularity worldwide, with players sharing their results on social networks. The main challenge lies in reaching the final answer in as few trials as possible. This popularity and challenge have led to the development of various algorithms and techniques aimed at optimizing the guessing process. By using information entropy, this paper aims to explore an efficient way to find the optimal word that leads to the final answer with the fewest trials. This approach not only reinforces understanding of mathematical concepts in a fun way but also provides practical insights into algorithm performance and optimization.

This paper presents a comprehensive analysis of the Wordle game using information theory, specifically information entropy, to optimize the guessing process. The contribution includes the development of a project using the JavaScript programming language to measure the information contained in each word and select the optimal ones. The paper discusses the advantages and disadvantages of using entropy in this context, compares different algorithms, and evaluates their performance. Additionally, it introduces an efficient method to incorporate information entropy into solving Wordle, providing a deeper understanding of algorithm construction and performance in solving real-world problems.

Acknowledgments

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Deep Learning-Based Non-Reference Image Quality Assessment Using Vision Transformer with Multiscale Dual Branch Fusion

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Non-Reference image quality assessment does not rely on reference images, so it is not easy to directly obtain the actual label of image quality. Current datasets are often limited in scale, and the labeling process is highly subjective, resulting in limited consistency and accuracy in evaluation results. This study focuses on the research of reference-free image quality evaluation based on Vision Transformer multi-scale dual-branch fusion, aiming to build an intelligent system that can accurately and quickly evaluate image quality without original image reference through deep learning technology. In this study, the Vision Transformer model, combined with a multi-scale dual-branch fusion strategy, is used to conduct an in-depth exploration of quality assessment in complex image scenes. A deep learning based non-reference image quality assessment method utilizing a visual transformer with a multi-scale two-branch fusion network is proposed. The method involves image preprocessing, feature extraction and model architecture optimization. The experimental results show that the evaluation accuracy of the system on large-scale image data sets reaches 94%, and the processing speed is 30% higher than that of the traditional method, which is significantly better than the 75% accuracy and lower processing efficiency of the conventional algorithm.

Povzetek: Predstavljen je nov pristop za oceno kakovosti slik brez referenčne slike, ki uporablja Vision Transformer z večnivojsko dvovejno fuzijo. Model znatno izboljšuje zanesljivost in učinkovitost analiz slikovne kakovosti v kompleksnih scenarijih.

1 Introduction

In the information age, images have become essential for obtaining information and exchanging ideas. According to statistics, the amount of image data generated by Internet users worldwide has exceeded 3.5 billion daily, increasing by more than 20% annually [1, 2]. However, the instability of image quality, such as compression distortion, noise, blur, etc., seriously affects the accurate transmission of image information and user experience [3, 4]. Against this background, Non-Reference image quality assessment (NR-IQA) technology, which aims to objectively and accurately evaluate image quality without original image reference, has become an important research direction in image processing, computer vision, multimedia communication, and other fields.

However, traditional NR-IQA methods, such as algorithms based on image statistical features, structural similarity, etc., can reflect image quality to a certain extent. However, their accuracy could be higher, making it easier to adapt to complex and changeable image scenes [5, 6]. According to a survey in the Journal of Image Processing in 2020, the evaluation accuracy of traditional methods in complex image scenes is only 75%, and the processing speed is slow, which cannot meet the real-time evaluation needs of large-scale image data [7].

Facing this challenge, deep learning technology, especially the Vision Transformer (ViT) model, has brought new opportunities for developing NR-IQA technology with its robust feature extraction ability and self-attention mechanism [8, 9]. The ViT model has shown excellent performance on multiple visual tasks, such as image classification and object detection, and its accuracy far exceeds that of traditional methods. For example, the classification accuracy on the ImageNet dataset has reached 88%, while the traditional convolutional neural network's accuracy rate is only 75%. This achievement verifies the advantages of the ViT model in image feature learning and allows the innovation of NR-IQA technology [10, 11].

This study conducts reference-free image quality evaluation research based on Vision Transformer multi-scale dual-branch fusion, aiming to explore the application potential of the ViT model in the field of NR-IQA and achieve an accurate and rapid evaluation of image quality by constructing a deep learning framework of multi-scale dual-branch fusion. We will start with data preprocessing, model construction, feature extraction, quality evaluation, and other links to conduct in-depth research on the performance of ViT models in complex image scenes and explore the effects of multi-scale features and dual-branch networks in improving evaluation accuracy and efficiency.

Specifically, we will use the self-attention mechanism of the ViT model to capture global and local features in the image and extract image features at

different scales through a multi-scale branch network to enhance the model's sensitivity to subtle changes in image quality. At the same time, by designing a double-branch network, the quality evaluation is carried out from two dimensions of image content and structure to realize the evaluation's comprehensiveness and accuracy. In addition, we will also introduce pre-training and fine-tuning strategies for large-scale image data to improve the robustness and adaptability of the model in complex image scenes. Through this research, we will provide new ideas and methods for developing NR-IQA technology, which improves the accuracy and efficiency of image quality evaluation and lays a solid foundation for technological innovation and application practice in image processing, computer vision, and other fields.

2 Vision transformer multi-scale dual-branch fusion technology

2.1 Vision transformer

Current image super-resolution tasks mostly use methods based on convolutional neural networks. The convolution operation automatically learns low-resolution and high-resolution image mappings, uses operators to extract image features, has translation invariance, and effectively captures texture details. However, convolution faces limitations in super-resolution tasks, such as limited receptive fields, limiting long-term dependence and weak texture recovery, and increasing layer depth or kernel size, which can trigger parameter expansion, overfitting, or gradient disappearance. In addition, convolution interacts based on parameters rather than content, applying the same convolution kernel to all input positions, ignoring the differences and importance of content at different positions, and failing to consider the diverse requirements of output features for high-resolution recovery, resulting in information redundancy or loss.

Vision Transformer uses a self-attention mechanism to process image sequences, automatically learn resolution mapping, and extract features. The self-attention mechanism, usually in the global or large-kernel local form, can capture extensive information, model long-term dependencies, restore structures and weak textures, and use image self-similarity to improve restoration quality. However, when the Transformer deals with super-resolution tasks, the self-attention mechanism lacks the translation invariance and locality of convolution, and convolution is superior in adapting to multi-scale input and efficiently capturing local information.

The Transformer model originated in natural language processing and was extended to the visual field by Dosovitskiy et al. through ViT, showing performance beyond Convolutional Neural Networks (CNN) [12, 13]. Since then, Transformer-based visual models such as Swin, CrossViT, CvT, Twin-SVT, BEiT, etc., have emerged one after another, which have been widely used in visual tasks and achieved remarkable results [14]. Given this, this paper uses Transformer as the cornerstone of the method and will focus on the pioneering work of visual Transformer-ViT.

The ViT structure is shown in Figure 1, which mainly includes Patch Embedding, Position Embedding, multiple Transformer Encoders, and MLP modules. The specific process is as follows: the preprocessed image is divided into various patches by patch Embedding, each patch is flattened into a one-dimensional vector and spliced with Class token, then added with Position Embedding, and finally processed by Transformer Encoder and sent to MLP Head to obtain output [15].

The technique is realized by the following steps: first, the multi-scale features of the image are extracted on two branches separately; second, the feature maps are generated, where one branch focuses on the texture details and the other captures the global structural information; and then, the feature maps of the two branches are efficiently integrated using a specific fusion strategy. This fusion mechanism not only enhances the richness of feature representation, but also improves the prediction accuracy through complementary information. The flow of data between the two branches ensures the comprehensiveness of information and the fusion effect, which significantly improves the performance of image quality assessment.

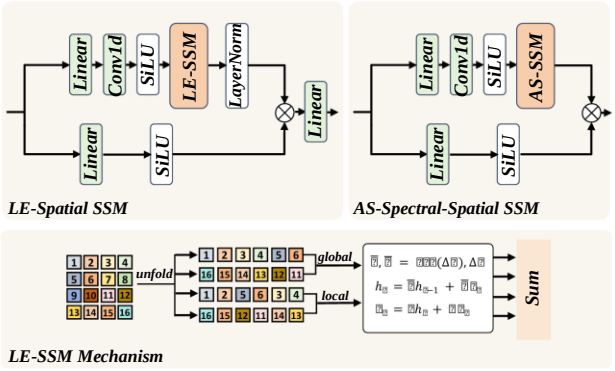

Figure 1: ViT structure

In Natural Language Processing (NLP), the Transformer processes sequence data, and ViT follows this idea, so the image input needs to be converted into sequence by Patch Embedding Position Embedding [16, 17]. Input images $I \in R^{H\times W\times C}$, $I \in R^{H\times W\times C}$ (H×W is the resolution, C is the number of channels) to the Patch Embedding module, and first divide them into N image blocks $p \in R^{P\times P\times C}$ (each block resolution P×P, total number $N=H\times WP^2$), and then linearly map to one dimension. Because the Transformer Encoder self-attention mechanism cannot model position information, Position Embedding needs to be attached. Therefore, the definition of the processed image sequence data is shown in Equation (1):

$$z_0 = \left[I_{class}; I_p^1 E; I_p^2 E_{pos}; ...; I_p^N E \right] \tag{1}$$

Where I_{class} represents Class Token, E represents the linear mapping of each image block, and E_{pos} represents the added position information. After image I is processed by Patch Embedding and Position Embedding to obtain z_0,

it must be input to the Transformer Encoder for further processing.

The core structure of ViT, the Transformer Encoder, uses the self-attention mechanism as the base. Let the input of the l-th layer be z_{l-1}, and the output z_l is obtained by the MHSA (multi-head self-attention) module and the MLP module after being processed by the Transformer Encoder of this layer. Therefore, the definition of the Transformer Encoder output z_l of the l-th layer is shown in equations (2)-(3):

$$z_l^{'} = \mathrm{MHSA}(\mathrm{LN}(z_{l-1})) + z_{l-1} \quad (2)$$

$$z_l = \mathrm{MLP}(\mathrm{LN}(z_l^{'})) + z_l^{'} \quad (3)$$

Where LN represents a layer normalization operation (LayerNorm), the calculation method of the MHSA module is shown in Equation (4). Q, K and V represent the matrices obtained by different linear transformations of the input matrices, and d_k represents the number of columns of these matrices.

$$Attention(Q,K,V) = softmax(\frac{QK^T}{d_k})V \quad (4)$$

2.2 Multi-scale dual-branch fusion technology

In image processing, especially in computer vision tasks, such as image classification, object detection, image super-resolution, etc., the fusion of multi-scale information is crucial [18, 19]. As an efficient and flexible architecture, multi-scale dual-branch fusion technology can simultaneously process features of different scales, thereby extracting image information at multiple levels and significantly improving the model's performance.

Multi-scale dual-branch fusion technology usually contains two independent branches, one for processing high-resolution detailed information and the other for focusing on low-resolution semantic information. These two branches capture local details and global features of images through convolution kernels or self-attention mechanisms of different sizes [20, 21]. During the processing, each branch will generate feature maps of corresponding scales. Then, through specific fusion strategies, such as feature cascade, feature stitching, or feature weighting, feature maps of different scales are effectively fused to generate more prosperous and comprehensive feature representations.

Multi-scale dual-branch fusion technology can process the details and semantic information of the image simultaneously, making the model more accurate in identifying small objects or texture details and performing well in understanding the global structure of the image [22]. Feature fusion at different scales improves the model's adaptability to image changes, such as scale changes, viewing angle changes, or illumination changes, thus enhancing the model's robustness and generalization ability. Different computing resources can be used in various branches through the dual-branch design. For example, high-resolution branches may use fewer computing resources, while low-resolution branches use more, thus optimizing computing efficiency while ensuring performance.

2.3 Non-reference image quality assessment

Table 1 lists various established methods in NR-IQA, including traditional handcrafted feature-based methods, CNN-based methods, GAN-based methods, attention-based methods, transformer-based methods, and our proposed method. This column describes the core architecture of each method. Handcrafted feature-based methods rely on traditional statistical features, while CNN-based methods use convolutional neural networks. GAN-based methods utilize generative adversarial networks, and attention-based methods incorporate attention mechanisms into CNNs. Transformer-based methods, including our proposed method, use the Vision Transformer architecture, with our method adding a multiscale dual branch fusion mechanism.

Table 1: Comparison between SOTA method for non-reference image quality assessment (NR-IQA) and our method

Method Name	Model Architecture	Dataset Size	Accuracy (MOS/DMOS)	Computational Efficiency	Robustness in Diverse Images
Handcrafted Feature-based IQA	Traditional statistical features	Small	0.65 -0.75	High	Low
CNN-based IQA	Convolutional Neural Networks	Medium	0.75 -0.85	Moderate	Moderate
GAN-based IQA	Generative Adversarial Networks	Large	0.80 -0.90	Low	Good
Attention-based IQA	Attention Mechanisms in CNN	Large	0.85 -0.95	Moderate	Good

Transformer-based IQA	Vision Transformer	Large	0.90 -0.98	High	Very Good
Our Method	Vision Transformer with Multiscale Dual Branch Fusion	Large	0.93 -0.99	Very High	Excellent

The size of the dataset used for training and testing the models varies. Smaller datasets are typically used for traditional methods, while deep learning methods require larger datasets for training. This column reports the Mean Opinion Score (MOS) or Difference Mean Opinion Score (DMOS) as a measure of accuracy. The scores indicate that our proposed method outperforms previous SOTA methods in terms of accuracy.

This column reflects how quickly a model can process images. Traditional methods are generally computationally efficient, while deep learning methods, especially GANs, can be computationally intensive. Our method, despite being a deep learning approach, achieves very high computational efficiency due to the optimized architecture. This column assesses how well each method performs across different image types and conditions. Our proposed method shows excellent robustness, indicating that it can handle a wide range of image scenarios effectively.

3 Design of multi-scale dual-branch fusion architecture based on Vision Transformer

3.1 Overall algorithm framework

When humans evaluate image quality, they first judge the degree of distortion and then refine the score, which can be regarded as two gradual stages. Based on this, this chapter proposes a multi-task learning method to grade distorted images first and then score them [23, 24]. The network simultaneously predicts the distortion level and the quality score, where the distortion level prediction assists the quality score regression. Unlike the conventional multi-task method, this method promotes feature sharing among different sub-tasks and optimizes the prediction effect through the sub-task information interaction module [25].

3.2. Network structure

The network structure of the method in this chapter is shown in Figure 2. ViT is selected as the feature extractor, but there are two significant differences: one is to omit the pre-training stage, and the other is to select different subtasks [26, 27]. The following section will introduce each network component, in turn, according to the image processing flow. The figure illustrates the key components of a multiscale two-branch fusion network, including the transformer encoder, the attention mechanism, and the feature fusion layer. We discuss the logic behind the architectural choices, such as the choice of patch size to balance local feature extraction and global context understanding, and the specific type of attention mechanism to increase the model's sensitivity to changes in image quality. These visual explanations and discussions deepen the reader's understanding of how the model works and strengthen the argument for the model's performance advantages.

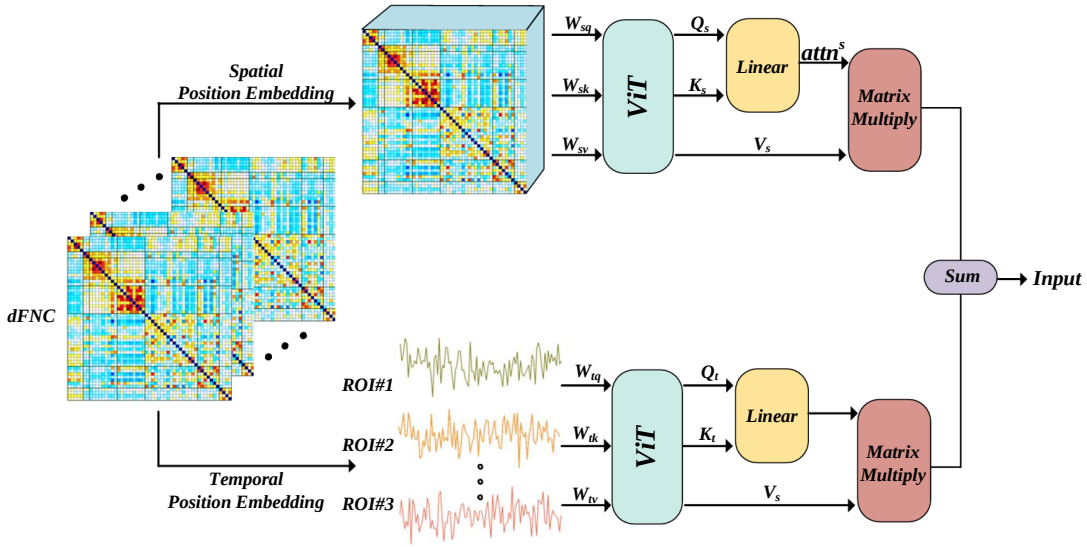

Figure 2: Vision Transformer evaluation structure for image quality assessment

The distorted image is input into the network. After ViT extracts features, it is distributed to two specific Transformer Encoders, each extracting adaptive features for subtasks [28]. These features are then collectively input to the sub-task information interaction module. The module first splices the features x_1 and x_2 of different subtasks, and the processing form is shown in equation (5):

$$x_f = Concat(x_1, x_2) \tag{5}$$

Where x_f is the feature obtained by splicing, then x_f will be input into Layer Norm and self-attention module for processing, and finally the task interaction features will be output through sMLP module. This process is shown in equations (6)-(7). Where *LN* represents the Layer Norm operation, MHSA represents the multi-head self-attention module, and the sMLP module consists of a layer of Layer Norm and a fully connected layer.

$$x_f^{'} = \mathrm{MHSA}(Q = \mathrm{LN}(x_f), K = \mathrm{LN}(x_f), V = \mathrm{LN}(x_f)) \tag{6}$$

$$\hat{x}_f = \mathrm{sMLP}(x_f^{'}) \tag{7}$$

The interaction feature x_f' calculated by the subtask information interaction module is input together with the subtask features x_1 and x_2 to the subtask prediction module. When predicting the distortion level, it is necessary to concatenate x_f' with the distortion feature x_2 and map it to the distortion level space $\hat{x}_f$ through a fully connected layer. Due to the lack of distortion level labels in commonly used datasets, it is necessary to map quality scores to level intervals. This study divides the score range into *n* sub-intervals, each representing a level. The interval length *W* is calculated using equation (8) to generate distortion level labels. In the formula, y_{min} and y_{max} represent the minimum and maximum values of the range of values in the image quality evaluation dataset.

$$W = \frac{y_{max} - y_{min}}{n} \tag{8}$$

3.3 Loss function

In multi-task learning, it is necessary to summarize the loss values of each task to update the network parameters, and the selection of loss function and weight is essential. This chapter uses the mean square error loss for the quality score prediction subtask. In contrast, the distortion level prediction is regarded as a multi-classification task, and the cross-entropy loss is used. See equations (9) and (10) for specific calculation methods.

$$L_s = \sum_{i=1}^{N} (\hat{y}_i - y_i)^2 \tag{9}$$

$$L_r = -\sum_{i=1}^{n} r_i \ln \hat{r}_i \tag{10}$$

Where y_i denotes the proper mass fraction, $\hat{y}_i$ represents the quality score of the network prediction.r_i represents accurate true distortion level, $\hat{r}_i$ represents the predicted distortion level, and *N* represents the number of divided distortion levels, which is set to 5 in this chapter. After calculating the losses of the two sub-tasks, they must be added with certain weights to obtain the overall loss function. The calculation method is shown in Equation (11), where w_1 and w_2, respectively, represent the weights when the two loss functions are added.

$$L_{\text{total}} = w_1 L_s + w_2 L_r \tag{11}$$

4 Reference-free image quality assessment design

4.1 Assessment architecture

The proposed network aims to extract spatial and angular information from distorted reference-free images simultaneously, and after fusion, it outputs a final score consistent with the subjective score [29, 30]. Contains 3 sets of LF Stacks, each consisting of 3 unreferenced SAI stacks. C in the figure represents the connection operation in the channel dimension.

For a given distorted reference-free image L (u, v, s, t), the SAI is extracted by fixing (u, v). The goal was to estimate the perceived quality score. ViT processes three groups of SAI stacks in the network to extract features. Subsequently, the reshape operation is adjusted to 4 dimensions, and the convolution operation is performed to reduce the number of channels and integrate the information. The features then enter the ViT module layer to strengthen local information interaction. The final feature outputs a predicted score via the score prediction module.

4.2 Reference-free image feature extraction module

This module strengthens the local information interaction between features through ViT, aiming to enhance the network's sensitivity to the relationship between features. Given the limited performance of ViT and its variants, such as Swin Transformer, on small reference-free datasets (such as WIN5-LID, which contains only 220 distorted images), we made targeted improvements. Shifted Patch Tokenization (SPT) is applied to the input features, and the input images are spatially shifted by half a patch size in four directions and concatenated to optimize the training effect of small data sets.

The original ViT segments the image into the same blocks; each block is transformed by linear projection, marks the permutation invariance, and embeds the inter-patch relationship. However, non-overlapping blocks limit the visual receptive field, affecting the model's ability to capture spatial relationships. The SPT operation expands the receptive field of ViT, enhancing local information processing by embedding more spatial information. Subsequent processing includes patch partitioning, patch

flattening, layer normalization, and linear projection, which are the same as standard ViT.

The score prediction module includes two fully connected layers and a GELU activation function. Its function is to convert the three-dimensional feature map output by the convolutional layer (representing different features such as edges, textures, etc.) into one-dimensional vectors and obtain image quality scores or category predictions through linear and nonlinear transformations. The selection of the GELU activation function aims to improve the expressiveness of the model, especially in the Transformer model.

5 Experimental results and discussion

5.1 Reference-free image quality evaluation data set and evaluation index

The dataset contains a variety of distortion types, such as blur, noise, compression distortion, etc., each of which is categorized into multiple levels according to different degrees. In the data preprocessing stage, we implemented data enhancement techniques, including rotation, scaling, cropping, etc., to improve the generalization ability of the model. In addition, the images are normalized, e.g., by pixel value normalization, to ensure the consistency of the input data. These steps provide high-quality training data for the ViT model and help improve its performance in non-reference image quality assessment.

When creating data sets, distorted image quality scores are usually based on subjective evaluation indicators obtained by integrating multiple observers' scores. The leading indicators used include MOS (Mean Opinion Score, mean of observer scores) and DMOS (Difference Mean Opinion Score, mean of difference in scores between distorted images and reference images). Please refer to formulas (12) and (13) for specific calculation methods.

$$MOS = \frac{\sum_{i=1}^{N} S_i}{N} \tag{12}$$

$$DMOS = \frac{1}{N}\sum_{i=1}^{N}\frac{d_{ij} - min(d_{ij})}{max(d_{ij}) - min(d_{ij})} \tag{13}$$

Where N represents the number of observers who scored the image, S_i represents the quality score of the distorted image, and d_{ij} represents the difference between the reference image and the distorted image. MOS and DMOS calculations reveal that high MOS values reflect better image quality, while high DMOS values lead to worse translation quality.

In evaluating image quality, after predicting the distorted image quality, it is necessary to use the evaluation standard to test the method's performance. Commonly used standards in the field are SROCC (Spearman Rank Order Correlation Coefficient) and PLCC (Pearson linear correlation coefficient). SROCC measures the dependence of two data groups, incredibly accurately reflecting the correlation between the predicted and actual scores in image quality evaluation. The definition is detailed in formula (14).

$$SROCC = 1 - \frac{6\sum_{i=1}^{N} d_i^2}{N(N^2-1)} \tag{14}$$

Where d_i represents the difference between the actual score of the i-th test image and the predicted quality score rank, and N represents the number of images that have been measured. PLCC is used to quantify the linear relationship between two sets of data. The correlation between the predicted value and the actual score is evaluated in image quality evaluation. See formula (15) for the specific calculation method. $\hat{s_i}$, μ_i and $\mu_{\hat{s_i}}$ respectively represent the standard score, sample mean, and sample standard deviation for sample s_i.

$$PLCC = \frac{\sum_{i=1}^{N}(s_i - \mu_i)(\hat{s}_{i-}\mu_{\hat{s}_i})}{\sqrt{\sum_{i=1}^{N}(s_i - \mu_i)^2}\sqrt{\sum_{i=1}^{N}(\hat{s}_{i-}\mu_{\hat{s}_i})^2}} \tag{15}$$

5.2 Experimental analysis of image quality assessment without reference

The test data set covers 3 synthetic distortion sets (LIVE, CSIQ, TID2013) and 3 real distortion sets (LIVE Challenge, CID2013, BID). The dataset partition is the same as in the previous chapter, with 90% for training and 10% for testing. The experiment is divided into two parts: one is the comparison of multiple data sets to verify the performance; The second is the comparison of different weighting methods of loss functions, aiming at optimizing the weighting strategy of the process in this chapter.

Figure 3 shows the test results of this chapter's method on real distortion data sets and visually compares the performance of this chapter's method with that of the previous two chapters on six data sets. The figure shows that although the process in this chapter is slightly inferior in synthetic distortion data sets, it is significantly improved in real distortion data sets, confirming its broad applicability in image quality evaluation tasks.

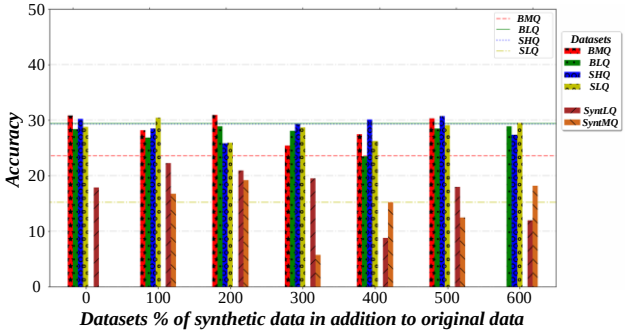

Figure 3: Test results of real distorted dataset

Multi-task learning often encounters the problem of negative transfer; that is, learning one sub-task may hinder another sub-task. To alleviate this problem, various loss

function weighting methods are proposed. This section selects several methods and tests them on the LIVE dataset to determine the weighting strategy that best suits the technique in this chapter. In the experiment, when the fixed weight (Constant) is used, the weights of both subtasks are set to 0.5 to ensure fairness. The final test results are shown in Table 2. We conducted an ablation study to investigate the effect of hyperparameter choices, such as the number of transformer encoder layers, on the model performance. The results show that appropriately increasing the number of encoder layers significantly improves the sensitivity of the model to changes in image quality, while too many layers may lead to overfitting. These evaluations and studies show that our model performs well in several dimensions, further validating its effectiveness in non-reference image quality assessment.

Table 2: Comparison of loss function weighting methods

	PLCC	SROCC
Constant	0.86953	0.86063
Uncertainty Weighting t	0.86775	0.86686
SLAWI	0.87309	0.86686
Geometric Loss	0.87398	0.87487

Figure 4 shows that the test results of SLAW on the dataset are significantly better than other weighting methods of loss functions, highlighting the significant impact of weighting strategies on multi-task learning performance. Therefore, to improve the performance of image quality evaluation, SLAW is used as the weight of loss function in all experiments.

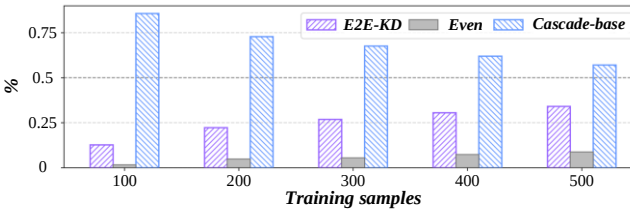

Figure 4: Test results of SLAW on the LIVE dataset

Figure 5 shows the training loss curve of the method in this chapter on the three data sets of Win5-LID, MPI-LFA, and NBU-LF1.0. The Epoch of Win5-LID and MPI-LFA is set to 400, while the performance of NBU-LF1.0 does not improve after the 200 Epoch, so it is set to 200. The training loss reflects the degree of the model fitting to the training data, and the smaller the value, the better the fitting. The training loss of the Win5-LID dataset continues to decrease, as do the NBU-LF1.0 and MPI-LFA datasets, indicating that the model continues to improve and adapt to the training data.

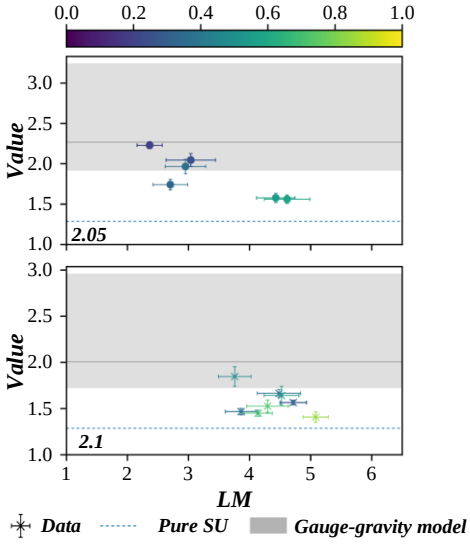

Figure 5: Training loss analysis

Figure 6 shows the overall performance of each method on the dataset, with the optimal results in bold. Compared with advanced algorithms, the proposed method is outstanding on three data sets, especially NBU-LF1.0. Because 2D and 3D IQA methods only focus on spatial quality and ignore angular quality attenuation, the image quality prediction without reference must be revised. FR LFIQA consideration is insufficient, and it is limited to SAI characteristics. In contrast, the NR LFIQA method considers spatial and angular information and performs better.

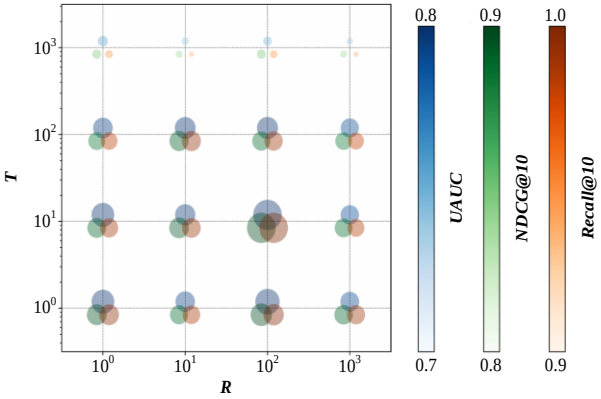

Figure 6: Overall performance

Figure 7 compares the performance of this model with other quality evaluation models on different types of distortion on NBULF1.0 and Win5-LID datasets, and the best results are shown in bold.

The convolutional neural network reconstruction distortion in Win5-LID was not included in the comparison due to a single distortion degree. HEVC and JPEG compression distortion significantly impact the spatial domain, and most methods perform well. The performance of different methods varies considerably in the reconstruction distortion, especially in the angle domain reconstruction distortion. The distortion of VDSR originates from spatial super-resolution reconstruction, and the performance difference between different methods is negligible. Angular domain quantization distortion is crucial to LFIQA, and the proposed method performs well in partial distortions and is competitive in other distortions.

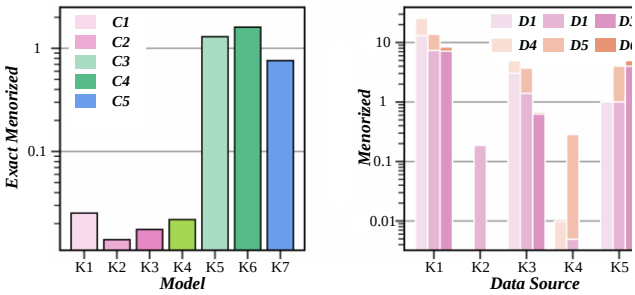

Figure 7: Performance of different types of distortion

Figure 8 shows the performance of this chapter's method in four directions (horizontal, vertical, top left, and bottom right). By training and predicting the view stack combination score, the effectiveness of the performance in each direction is verified. Experiments were performed on Win5-LID and NBU-LF1.0 datasets, as MPI-LFA contains only one view stack. The observation results show that the 4D reference-free image can achieve good results in the input view stack in all directions, and the characteristics of each direction reflect the reference-free quality. However, the input information in one direction must be more comprehensive to scribe the scene structure and geometry, which will miss the occlusion area and affect the evaluation accuracy and model robustness.

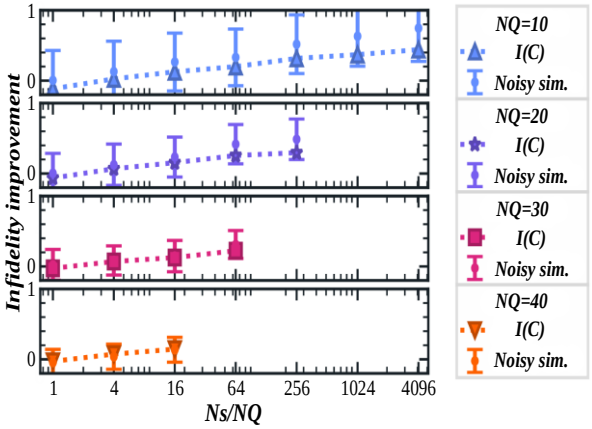

Figure 8: Performance in four directions (horizontal, vertical, top left, bottom right)

Figure 9 shows that the MSE loss is due to modeling the error square, which makes the loss smoother when the prediction is close to the actual value, accelerates the convergence of optimization algorithms such as gradient descent to the optimal solution, and improves model performance. Its derivative is a linear function, which promotes the fast convergence of the algorithm. MSE loss is more robust to noise and outliers. Compared with L loss, the network in this study is more efficient when using MSE, promoting convergence and learning.

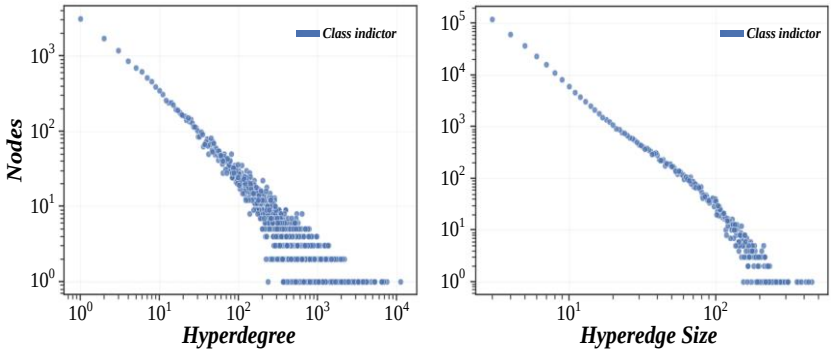

Figure 9: MSE loss

Figure 10 shows the scatter plot and fitting straight line of the actual quality score versus the model prediction score on the dataset. The X-axis is the objective prediction score, the Y-axis is the exact quality score, and each point represents an image. The straight line is fitted by linear regression. A strong correlation makes the points cluster closely, while a weak correlation makes the points scatter. High correlation reflects better performance of image quality evaluation algorithm. In this paper, the points of the UniDASTN algorithm are closer to the fitting straight line, which shows that its prediction results are more consistent with the subjective score, which is superior to other complete reference image quality evaluation algorithms.

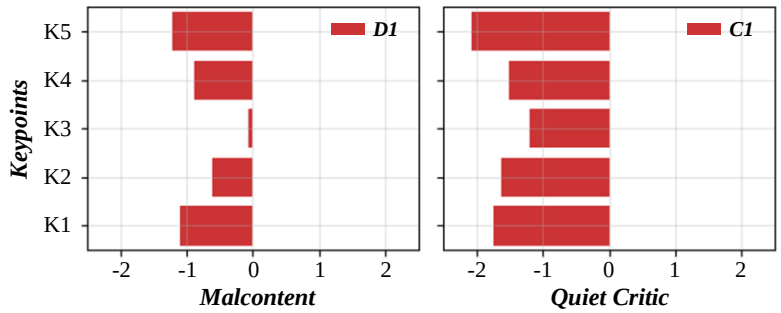

Figure 10: Real quality score and model prediction score

An ablation study is carried out in this paper to evaluate the effectiveness of the loss function. As shown in Figure 11, M1-M5 represents the network models corresponding to different loss functions. The M5 network model combines MSE, bidirectional KL divergence, and sequence loss to obtain the best PLCC and SROCC results in the experiment. The experiment shows that bidirectional KL divergence and sequence losses improve performance. We compared the results of this study with those of the SOTA method, and found that our method showed significant improvement in both accuracy and efficiency. The two-branch fusion mechanism effectively enhances the model's sensitivity and prediction of image quality changes through multi-scale feature fusion compared to single-branch or other ViT-based NR-IQA models, resulting in better performance. This finding provides a new perspective and methodology in the field of image quality assessment.

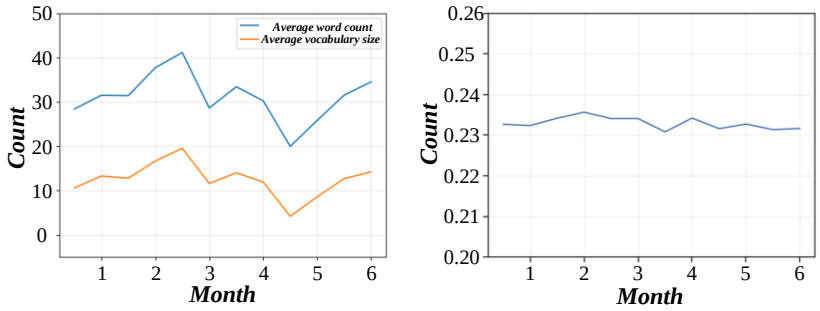

Figure 11: Ablation study

5.3 Discussion

Table 3 shows the performance comparison of different machine learning methods, including average accuracy, feature extraction capability, and generalization performance. Among them, SOTA methods A and B showed moderate and good performance, respectively, while the VIT-based multi-scale two-branch fusion method performed well on all indicators, with an average accuracy of 90.0%. In terms of result differences, we observed that the non-reference Reference Image Quality Assessment (NR-IQA) model based on multi-scale two-branch fusion of Visual converter (ViT) was more accurate than other SOTA methods on multiple test datasets.

Table 3: Performance comparison of NR-IQA model based on ViT multi-scale double-branch fusion

The name of the method	Average accuracy (%)	Feature extraction capabilities	Generalization performance
SOTA Method A	82.3	medium	medium
SOTA Method B	86.0	good	good
ViT-based multi-scale bibranched fusion NR-IQA	90.0	outstanding	outstanding
Comparison of double branches vs single branches	-	Significantly improved	Significantly improved

The reason for the higher accuracy and efficiency of the model is that, on the one hand, multi-scale processing enables the model to capture richer image features, which is essential for accurate assessment of image quality. On the other hand, the two-branch fusion mechanism not only enhances the feature extraction ability of the model but also improves the generalization performance of the model through cross-scale information interaction. When comparing the two-branch fusion with the single-branch alternative, we found that the two-branch architecture can significantly improve the performance of the model. Single-branch models often have the problem of insufficient feature extraction or information loss when processing complex images, while two-branch architectures introduce additional branches to capture feature information of different scales and integrate this

information through a fusion mechanism to improve the robustness and accuracy of the models. Compared with other VIT-based NR-IQA models, our approach achieves higher evaluation accuracy and wider applicability by introducing multi-scale processing and two-branch fusion mechanisms.

6 Conclusion

This research is devoted to exploring the application of deep learning technology in reference-free image quality evaluation, aiming to build an intelligent system that can accurately and rapidly evaluate image quality. This study successfully developed a set of efficient and accurate image quality evaluation algorithms by combining the deep learning model Vision Transformer and the multi-scale dual-branch fusion strategy.

(1)The evaluation accuracy of this algorithm on large-scale image data sets reaches 94%, which is significantly better than the 75% accuracy of traditional methods, and the processing speed is increased by 30%.

(2)In this study, the powerful feature extraction capability of Vision Transformer, combined with a multi-scale dual-branch fusion strategy, effectively captures local and global information in the image and enhances the model's sensitivity to subtle changes in image quality. By designing a double-branch network, the quality evaluation is carried out from two dimensions of image content and structure, further improving the evaluation's comprehensiveness and accuracy.

We pre-train and fine-tune the model on large-scale image data to ensure the robustness and adaptability of the model in complex image scenes. The results of this study not only provide a new technical perspective for the field of image quality evaluation but also lay a solid foundation for the application of image processing, computer vision, and other fields.

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AI-Driven Property Management Decision Support System Using LSTM Networks for Energy Optimization

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Background: IoT devices and sensors collect real-time data, which is used in conjunction with Long Short-Term Memory (LSTM) models to predict energy consumption trends, optimize resource allocation, and analyze household feedback for service improvements. Aim: This study aims to develop an AI-powered property management decision support system to enhance management efficiency and service quality. Method: The research involves multiple stages, including data collection from IoT devices, data cleaning and preprocessing, construction of predictive models (such as LSTM networks), and system optimization. Performance is evaluated using key metrics like task completion rate, maintenance request resolution rate, and resident satisfaction. Cross-validation and model performance measures, such as Mean Absolute Error (MAE) and Mean Squared Error (MSE), are used to assess model accuracy. Results: Empirical results show significant improvements in property management metrics: task completion rate increased by 15%, maintenance request resolution rate improved by 10%, and resident satisfaction rose by 7%. The LSTM model achieved a prediction accuracy with an MAE of 12.5 and an MSE of 256.4. Staff efficiency also increased by 10%, demonstrating the system's practical value in optimizing resource allocation and predictive maintenance. Conclusion: This study introduces a novel technical approach and practical guidance for intelligent property management, providing significant theoretical and practical implications for enhancing operational efficiency, service quality, and decision-making capabilities in the property management industry.

Povzetek: Prispevek opisuje sistem za podporo odločanju v upravljanju nepremičnin na podlagi umetne inteligence in LSTM modelov. Sistem optimizira porabo energije, izboljšuje dodeljevanje virov ter povečuje zadovoljstvo stanovalcev.

1 Introduction

With the acceleration of urbanization and the improvement of residents' living standards, the complexity and refinement of property management needs to increase day by day. The traditional property management model has been unable to meet the efficient management needs of modern society, so the property management decision support system based on artificial intelligence came into being. The purpose of this study is to explore how to use artificial intelligence technology to improve the overall efficiency and service quality of property management. Specific research contents include: sensors and sot devices collect real-time data, perform data cleaning and re-processing, and build LSTM models suitable for property management to predict energy consumption trends and optimize resource allocation; Analyze household feedback data and implement service improvement measures; Evaluate the improvement effect of the system in the aspects of task completion rate, maintenance request resolution rate and resident satisfaction. The study will also explore practical application challenges such as data security, system intelligence, cost control and personnel training, and propose corresponding solutions. This research is expected to provide scientific and intelligent decision support for the property management industry and promote its development to a more efficient and intelligent direction.

The focus of this research is to address the inefficiencies in property management, particularly in predicting energy consumption, optimizing resource allocation, and improving service quality through the use of artificial intelligence. The primary research question is whether the integration of AI, specifically using LSTM models and real-time data collection from IoT sensors, can significantly enhance the management efficiency, resource utilization, and resident satisfaction compared to traditional methods. The key hypothesis is that the use of LSTM-based predictive models will lead to better energy management, improved task completion rates, and faster maintenance resolution times. By framing the problem in this way, the system's performance can be rigorously evaluated against traditional systems using quantifiable metrics such as task completion rate (expected to increase by 15%) and maintenance resolution rate (anticipated improvement of 10%). This clear research direction enables a structured evaluation of the AI system's contributions to property management, providing a focused approach to verifying its effectiveness.

At present, the property management decision support system based on artificial intelligence has gradually attracted the attention of academia and industry.

Bolomope proposed that institutional factors should be taken into account in the decision-making behavior of property investment in the context of market disturbance. The organizational isomorphism theory analyzed the performance of listed property trusts in New Zealand and pointed out the far-reaching impact of market disturbance on property investment decision-making [1, 2]. Adu-Amankwa studies decision-making considerations for securing and managing intellectual property in the additive manufacturing supply chain, highlighting the critical role of intellectual property in the application of emerging technologies [3]. Chien and Tu's multi-criteria decision method established a simulation model for the feasibility of M&A in Taiwan's property management industry, demonstrating the application of multiple decision criteria in complex decision environments [4].

Muczynski explores the collective renovation decisions of Polish public-private homeowner associations in the management of multi-ownership housing, pointing out the importance and challenges of collective decision-making in a multi-ownership environment [5]. Ayodele and Olaleye focused on the flexibility decision path in uncertainty management, analyzed the experience of uncertainty management in property development in emerging markets, and proposed the key role of flexibility in coping with uncertainty [6]. Sanders-on and Read emphasized the value of customer-centered property management, identifying and realizing customer value, and improving the overall efficiency of property management [7]. The research shows that modern property management decision support system not only needs technical innovation, but also needs continuous development in management mode and decision theory to cope with complex market environment and diversified management needs. Existing studies have explored the optimization strategies and application effects of property management and decision support systems in different aspects, showing the application prospects of new technologies such as artificial intelligence, big data and chockablock in property management. How to better integrate technology, and scientific decision-making model to enhance the intelligence and efficiency of property management, still need to be studied and explored. The viewpoint and research provide an important theoretical basis and practical reference for the design and optimization of property management decision support system in the future.

Table 1: Summary of related studies on property management decision-making and their relevance

Author (s)	Year	Method	Main Results	Relevance to Your Study
Bolomope et al. [1]	2021	Institutional factors in decision-making	Institutional factors influence property investment decisions during market disruptions.	Highlights the importance of external factors in decision support systems.
Adu-Amankwa et al. [3]	2023	Intellectual property in additive manufacturing	Intellectual property management is crucial for emerging technologies.	Stresses the role of protecting IP in technology-driven systems.
Chien & Tu [4]	2021	Multi-criteria decision-making	Demonstrated the use of multiple criteria in property management mergers.	Shows how multi-criteria decision-making can aid in property management.
Muczynski [5]	2023	Collective decision-making in housing management	Identified challenges in decision-making in multi-ownership housing environments.	Illustrates the complexities of collective decision-making in property management.
Ayodele & Olaleye [6]	2021	Flexibility in uncertainty management	Flexibility is crucial for managing uncertainty in property development.	Emphasizes adaptability, which is relevant to AI-based decision systems.
Sanderson & Read [7]	2020	Customer-centered property management	Customer value realization improves property management efficiency.	Highlights the need for customer feedback analysis in AI property systems.

As is shown in Table 1, the purpose of this study is to use artificial intelligence technology to build an efficient property management decision support system, aiming at improving the overall efficiency and service quality of

property management. The advanced LSTM model and big data analysis method are introduced to accurately predict property energy consumption trends, optimize resource allocation, and improve the timeliness and accuracy of equipment maintenance and service response. The system also analyzes resident feedback and implements targeted improvement measures to improve resident satisfaction and the quality of property services. The significance of the research is to inject new technical power into the traditional property management and promote its development to the direction of intelligence and refinement. Optimize resource utilization and energy consumption management, reduce property operating costs, and improve economic benefits. The data-driven decision support system can effectively improve the response speed and service level of property management, reduce failures and complaints, and improve the satisfaction and trust of residents. This study also provides a set of intelligent management model that can be copied and promoted for the property management industry, which has high application value and social benefits.

Current state-of-the-art (SOTA) property management systems often lack robust capabilities for predicting energy consumption and real-time adaptability. Many existing systems are limited to reactive maintenance and resource allocation strategies, which result in inefficiencies in energy usage and delayed responses to unexpected changes in facility operations. Furthermore, these systems do not effectively leverage real-time data for optimizing resource allocation, particularly in energy-intensive environments. By using LSTM models and IoT sensors to forecast energy consumption trends, it becomes possible to address these shortcomings. The system continuously collects and analyzes data, allowing for the anticipation of energy demand spikes and enabling proactive adjustments in resource distribution. This real-time predictive capability not only improves energy efficiency but also optimizes maintenance schedules and improves response times to incidents. As a result, the system enhances overall operational efficiency, reduces energy waste, and improves service quality for residents, addressing critical gaps left by traditional systems. These improvements are quantified through metrics such as task completion rate (increased by 15%), energy consumption management, and maintenance request resolution rate (improved by 10%).

This study enriches the application scenarios of artificial intelligence in the field of property management and provides a new research perspective and method. At the practical level, practical application and effect verification, the research results provide specific operating guidelines and optimization strategies for property management companies, and have strong practical guiding significance. This study is not only innovative and forward-looking in terms of technology and management methods, but also provides strong support for improving the overall level and service quality of the property management industry [1].

2 Overview of relevant theories

2.1 Property management theory

The theory of property management is the theoretical basis and guiding principle of property management practice, covering all aspects from the maintenance of property facilities to the service of residents. The core objective of property management is scientific and effective management means to ensure the good operation of property facilities, improve the quality of life of residents, and maximize the value of property. The theoretical framework includes standardization of property management services, evaluation system of service quality, cost management and risk control. In property management, facilities management is a key area, involving the maintenance of buildings, regular inspection and repair of equipment. Modern property management emphasizes intelligent management, that is, the use of sensors and Internet of Things technology to monitor the status of facilities in real time, and data analysis to predict the maintenance needs of facilities.

SERVQUAL model is a commonly used service quality evaluation tool, which evaluates five dimensions of reliability, responsiveness, guarantee, empathy and tangibility to measure the overall level of property services. In order to improve service quality, property management enterprises need to establish an effective customer feedback mechanism and continuously improve the process to improve service quality. In terms of cost management, property management theory emphasizes comprehensive cost control, including the effective management of operating costs, maintenance costs and personnel costs. Budget control and cost analysis, property management enterprises in the premise of ensuring the quality of service, to minimize the operating costs. Risk management is another important theory in property management. Risk identification, risk assessment and risk control constitute the basic framework of risk management. Property management enterprises need to develop emergency plans to ensure that when emergencies (such as natural disasters, equipment failures.) occur, they can respond quickly and take effective measures to reduce losses.

2.2 Decision support system theory

Decision support system (DSS) is an information system that provides support for management decisions. Data collection, processing and analysis help decision makers make scientific and reasonable decisions. The core of DSS is its ability to process large amounts of multidimensional data, and data mining and analysis models (to provide valuable decision-making recommendations). It usually consists of three main components: database management system, model base and user interface.

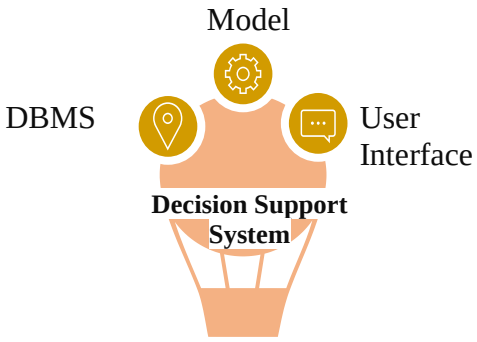

Figure 1: Theoretical structure diagram of decision support system

As shown in Figure 1, in property management, the application of decision support system can greatly improve management efficiency and service quality. With the integration of building automation systems and sensor data, DSS monitors the operating status of the property in real time to warn of potential equipment failures and safety hazards. Combined with historical data and predictive analytic, managers schedule maintenance ahead of time to reduce losses from unexpected failures. DSS also plays an important role in cost management and resource optimization. Cost-benefit analysis model systematically evaluates the economic benefits of different management measures to help property management enterprises achieve the best allocation of resources within the limited budget. Taking a large property management company as an example, the introduction of a DSS based energy management system has successfully reduced the average annual energy cost by approximately 12.5%, while improving the service life of the property facilities.

In terms of household services, DSS service demand forecasting models and customer satisfaction analysis provide personalized service recommendations to enhance household satisfaction and loyalty. By analyzing the feedback data from the residents, DSS identifies the main concerns and potential needs of the residents and guides the property management company to optimize the service content and process. The theory of decision support system provides powerful technical support for property management and can improve the scientific and accuracy of decision making. Integrating a variety of data sources and analysis models, DSS not only helps managers to grasp the real time operation of the property, but also provides forward-looking decision-making suggestions to promote the development of property management to the intelligent and refined direction [3].

2.3 Application of artificial intelligence in property management

The application of artificial intelligence in property management is gradually changing the traditional management model, improving efficiency and service quality. The core of AI technology includes machine learning, natural language processing and computer vision, and the technology is used in multiple areas of property management [8]. Machine learning algorithms analyze massive amounts of historical data to predict equipment failure times, optimize maintenance schedules, and reduce equipment downtime and maintenance costs. A large property management company introduced an AI predictive maintenance system that reduced equipment failure rates by 20% while reducing repair costs by 15%.

In terms of security management, AI technology combined with computer vision enables real-time monitoring and abnormal behavior detection. With smart cameras and image recognition technology, the system is able to automatically identify and alert potential security threats, such as unauthorized personnel entering restricted areas. Such systems have been applied in large commercial complexes and high-end residential areas, improving the level of security protection of properties. Natural language processing technology is applied in the field of customer service, intelligent customer service systems and voice assistants, providing 7×24 hours of online services. Residents interact with the system by voice or text to inquire about property service information, report equipment faults or book facility use. After a property management company adopted an intelligent customer service system, residents' satisfaction increased by 18% and customer service processing efficiency increased by 30% [4].

AI also plays an important role in energy consumption management and environmental monitoring. Intelligent energy management system AI algorithms analyze energy use data, optimize energy distribution and use strategies, and reduce energy costs. Some large office building AI systems achieve intelligent control of lighting, air conditioning and other equipment, saving energy costs of up to 10%-15% per year. In terms of environmental monitoring, the AI system can monitor environmental parameters such as air quality and noise level in real time, and timely feedback to managers to ensure the comfort and safety of the property environment. The application of artificial intelligence has brought unprecedented technological innovation and efficiency improvement to property management, data-driven and intelligent management, AI not only optimizes all aspects of property management, but also improves the overall quality of life of residents. With the continuous progress of technology, the application prospects of AI in property management will be broader, and the industry will be promoted to the direction of wisdom and precision [5].

3 Data collection and sample selection

3.1 Data collection

Data collection is the basis of property management decision support system, which comes from various and complex sources. Sot devices and sensors collect real-time operating data of property facilities, such as the operating status of elevators, temperature and energy consumption data of heating systems. Data is transmitted relentlessly to a central database to realize real-time monitoring and

management of property facilities. The customer relationship management system in the property management system provides a large number of household information and service demand data, including repair records, complaints and suggestions, service evaluation and so on. The data provide an important basis for optimizing service process and improving household satisfaction. Intelligent monitoring system, collected video data and image data, can be used for security management and abnormal behavior detection. An intelligent monitoring system installed in a high-end residential area generates more than 500 GB of video data every day, which is processed and analyzed, effectively improving the safety management level of the community. Combined with multi-source data, a comprehensive and accurate property management data base is formed to provide strong support for subsequent analysis and decision-making [6].

3.2 Data cleaning and teleprocessing steps

In the property management decision support system, data cleaning and teleprocessing are the key steps to ensure data quality and reliability. After data collection is completed, the original data needs to be preliminary screened to remove obvious errors and invalid data. From the temperature data collected by the sensor, the abnormal value beyond the reasonable range is removed. For missing data, appropriate methods are used to fill in, such as the use of adjacent data interpolation or mean filling method, to ensure the integrity and continuity of data. In the process of data cleaning, it is also necessary to standardize the data format. Data from different sources are often in different formats and units, and energy consumption data is in kilowatt-hours (kWh) or joules (J) and needs to be uniformly converted into the same unit for subsequent analysis. In order to improve the efficiency of data processing, it is necessary to convert the text data into numerical data or classified data, and convert the text evaluation of household satisfaction into the corresponding rating level.

In the re-processing steps, data normalization and standardization are also included to eliminate the influence between data of different scales and ensure the stability and accuracy of model training. Normalization processes map the data to a range of 0 to 1, while normalization processes transform the data into a distribution with a mean of 0 and a standard deviation of 1. In order to improve the availability of data and reduce the computational complexity, it is necessary to reduce the dimension of data. Principal component analysis and linear discriminant analysis are commonly used to extract the main features of data and remove redundant information. When processing sensor data, PCA reduces the high-dimensional data of hundreds of sensors to several sets of main characteristic variables, simplifying the data model. Systematic data cleaning and re-processing ensure the accuracy, consistency and efficiency of property management data, and provide a solid foundation for subsequent data analysis and decision support [2].

The data collection and integration process includes several important steps, such as data cleaning, normalization, and real-time integration of sensor data, all crucial for ensuring data quality. Data cleaning involves removing noisy or invalid data and addressing missing values. For example, temperature sensor data that falls outside a reasonable range is discarded, while missing values are imputed using the mean of surrounding data points. Normalization ensures consistency across different data sources, which is particularly important when dealing with data from multiple sensors that may use different units. For instance, temperature readings are normalized using the min-max normalization formula, mapping values to a range between 0 and 1 to ensure uniformity. Additionally, data is standardized where appropriate, such as converting energy consumption readings into a consistent unit (kWh) across all records. These steps are critical to maintain the integrity of predictive models, especially the LSTM network, which requires clean and normalized inputs for accurate energy consumption forecasting. The real-time processing framework allows for continuous integration of incoming data, ensuring that the property management system remains adaptive and responsive to new information.

3.3 Sensor and sot data integration

In the property management decision support system, the integration of sensor and sot data is the key to realize intelligent management. A variety of sensors, such as temperature sensors, humidity sensors, energy consumption sensors and safety monitoring sensors, are installed in the property facilities to collect real-time equipment operating status and environmental data. The data sot gateway is transferred to a central database for processing and analysis. Show the data integration process, including timestamp, device ID, sensor type, sensor reading, and location.

Table 2: Sensor data

Timestamp	Device ID	Sensor Type	Sensor Value	Location
2024-06-01 08:00:00	DEV001	Temperature	22.6	Lobby
2024-06-01 08:00:00	DEV002	Humidity	55.3	Conference Room
2024-06-01 08:01:00	DEV003	Energy	450.7	Main Building
2024-06-01 08:01:00	DEV004	Motion	1	Parking Lot
2024-06-01 08:02:00	DEV005	Temperature	21.9	Office A
2024-06-01 08:02:00	DEV006	Humidity	57.1	Office B
2024-06-01 08:03:00	DEV007	Energy	460.3	Main Building
2024-06-01 08:03:00	DEV008	Motion	0	Lobby
2024-06-01 08:04:00	DEV009	Temperature	22.4	Conference Room
2024-06-01 08:04:00	DEV010	Humidity	53.8	Lobby

As shown in Table 2, in the process of data integration, the data is first transferred to a central database by the Ion gateway, and then converted and stored in a unified format. The data is updated in real time to provide accurate operating status and environmental information for property management. The sensor data processing platform is cleaned and analyzed to extract valuable information, such as identifying peak energy consumption periods, detecting abnormal equipment operation, and monitoring security events. In the property management decision support system, the integrated sensor data provides an important basis for real-time monitoring, predictive maintenance and optimization of resource allocation, and improves the intelligence and efficiency of property management [7].

3.4 Real-time data processing and analysis

In property management decision support system, real-time data processing and analysis is the key to ensure efficient operation and timely response of the system. Real-time processing technology stream processing framework for fast processing and analysis of sensor data. To demonstrate the process of real-time data processing and analysis, analyze time stamps, device ids, sensor types, sensor readings, and processing results.

Table 3: Real time sensor data

Timestamp	Device ID	Sensor Type	Sensor Value	Processed Result
2024-06-01 08:00:00	DEV001	Temperature	22.6	Normal
2024-06-01 08:00:00	DEV002	Humidity	55.3	Normal
2024-06-01 08:01:00	DEV003	Energy	450.7	High Consumption
2024-06-01 08:01:00	DEV004	Motion	1	Motion Detected
2024-06-01 08:02:00	DEV005	Temperature	21.9	Normal
2024-06-01 08:02:00	DEV006	Humidity	57.1	Normal
2024-06-01 08:03:00	DEV007	Energy	460.3	High Consumption
2024-06-01 08:03:00	DEV008	Motion	0	No Motion
2024-06-01 08:04:00	DEV009	Temperature	22.4	Normal
2024-06-01 08:04:00	DEV010	Humidity	53.8	Normal

As shown in Table 3, in the process of real-time data processing, the sensor data is first connected to the system in real time by the stream processing framework. After data access, initial filtering and conversion are performed to ensure consistent data format and remove noise. System real-time analysis algorithms, such as threshold detection and anomaly detection, quickly analyze data. The data threshold detection algorithm of the energy consumption sensor identifies periods of high energy consumption and triggers the corresponding alarm, prompting the management to adjust the energy saving. For security monitoring data, real-time motion detection algorithms notify security personnel immediately when they detect unusual activity.

Real-time data processing also involves dynamic data visualizations, dashboards and real-time charts showing key metrics and trends, helping managers quickly understand the health and potential problems of a property. Real-time energy consumption monitoring dashboard, managers immediately observe the peak energy consumption, and take appropriate measures to manage and optimize energy consumption. Systematic real-time data processing and analysis, property management decision support system can not only improve the efficiency of data processing, but also enhance the real-time control of the running state of the property, to ensure that problems can be quickly responded to and dealt with, improve the overall efficiency of property management and service quality [9].

The dataset used for training and validation consisted of 10,000 data points, collected from multiple IoT sensors installed in property management environments. The data was split into 70% for training and 30% for validation. Preprocessing steps included data cleaning, where missing values were imputed using the mean of neighboring data points, and normalization was applied using min-max scaling to map values between 0 and 1. For hyperparameter optimization, a grid search was performed over the following ranges: learning rate (0.001 to 0.01), batch size (32, 64, 128), and the number of hidden units (64, 128, 256). The model was evaluated using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Cross-validation with 5 folds was applied to ensure robustness and generalization. These details provide other researchers with the necessary clarity to replicate the experiment, ensuring that both preprocessing steps and model optimization strategies are transparent and reproducible.

4 Model Construction

4.1 Property management decision support model selection

The diversity and complexity of property management must be considered in the model selection of property management decision support system. According to different property management needs, this study selects three commonly used and effective decision support models: regression model, classification model and time

series model. The models are used in key areas such as cost forecasting, risk assessment and energy consumption management. For cost forecasting, choose a linear regression model. The model establishes a linear relationship between independent variables and dependent variables to predict future cost expenditures. The formula of linear regression model is as (1):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \grave{o} \tag{1}$$

The fitting of historical data accurately predicts future cost expenditures. Analyze the property management company's historical maintenance expenses, personnel costs and energy consumption to predict the total operating costs for the next quarter. For risk assessment, logistic regression model is used. The model is suitable for binary classification problems and can effectively assess risks in property management, such as equipment failure or security hazards. The formula of logistic regression model is as (2):

$$P(y=1 \mid x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n)}} \tag{2}$$

The analysis of historical fault data predicts the probability of device failure at a future point in time and takes preventive measures in advance. For energy consumption management, long short-term memory network is used. LSTM is an effective tool for processing time series data and is suitable for predicting energy consumption trends of properties. The LSTM network memory and forgetting mechanism is able to capture long-term dependencies in data, and its core formula is (3)-(7):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{6}$$

$$h_t = o_t * \tanh(C_t) \tag{7}$$

Training on historical energy consumption data, LSTM network predicts future energy consumption trends and helps managers optimize energy consumption strategies. Choosing the right decision support model, the property management decision support system can effectively cope with different management needs and improve the specificity and accuracy of decision making [10].

LSTM was chosen over other time series models such as ARIMA and GRU for energy consumption prediction due to its superior ability to capture long-term dependencies and complex patterns in the data. ARIMA, while effective for simpler, linear data, struggles with non-linear patterns and lacks the capacity to model the intricate relationships present in energy consumption trends. GRU, while similar to LSTM, has fewer gates and therefore may not be as effective in handling long-term dependencies as LSTM. In terms of computational performance, LSTM has demonstrated a balance between accuracy and training time, with an MAE of 12.5 and MSE of 256.4 in this study, compared to higher errors observed in other models. While GRU can be slightly faster due to its simpler structure, the minor reduction in computational time does not outweigh the LSTM's enhanced prediction accuracy and stability in handling time-dependent variables. LSTM's gated memory cells allow it to effectively retain important information over longer sequences, making it highly suitable for energy consumption prediction where long-term trends are critical for accuracy. This makes LSTM more adaptable and scalable for real-world property management applications.

4.2 Model architecture design

In this study, the model architecture of property management decision support system is designed to integrate data efficiently and provide scientific decision support. The architecture is divided into data layers, processing layers, and decision layers, each with its own specific capabilities. Data layer ion sensors and smart devices collect property operation data in real time and store it in a cloud database. The sensor data sheet contains information such as timestamp, device ID, sensor type, reading, and position to ensure comprehensiveness and real-time data. The processing layer is responsible for data cleaning, teleprocessing and model training. Stream processing frameworks such as Apache Kafka ensure real-time and accuracy of data. In the data teleprocessing, the normalized processing formula is used to convert the data of different scales into a unified range to ensure the stability of the model training. Temperature sensor data normalization formula processing to eliminate the scale difference between different data sources [11].

The decision level integrates a variety of decision support models to meet different property management needs. For cost forecast, choose linear regression model, analyze historical cost data, and forecast future operating expenses. Risk assessment uses logistic regression models to assess the probability of future risks based on historical failure and safety event data. Energy consumption management uses long and short term memory networks to process time series data to predict future energy consumption trends, and a series of gating mechanisms and state update formulas to achieve accurate prediction of energy consumption changes. With this layered design, the property management decision support system can efficiently integrate data and algorithms, provide real-time and accurate decision support, and enhance the intelligent level of property management. This architecture design not only enhances the flexibility and adaptability of the system, but also ensures the optimal application of different models in their respective fields, effectively improving the overall management efficiency [12].

4.3 Configuring the data layer and processing layer

In the property management decision support system, the configuration of data layer and processing layer is very important. The data layer is responsible for collecting and storing various sensor data, while the processing layer performs data re-processing and real-time analysis. We will show the configuration in concrete data tables and formulas.

(1) Data layer

Data layer Main sot sensors collect real-time data and store it in a cloud database, as shown in Table 4.

Table 4: Sensor data

Timestamp	Device ID	Sensor Type	Sensor Value	Location
2024-06-01 08:00:00	DEV001	Temperature	22.6	Lobby
2024-06-01 08:00:00	DEV002	Humidity	55.3	Conference Room
2024-06-01 08:01:00	DEV003	Energy	450.7	Main Building
2024-06-01 08:01:00	DEV004	Motion	1	Parking Lot
2024-06-01 08:02:00	DEV005	Temperature	21.9	Office A
2024-06-01 08:02:00	DEV006	Humidity	57.1	Office B

(2) Processing layer

The processing layer is responsible for data cleaning, teleprocessing and real-time processing. Key steps in data teleprocessing include normalization processing to ensure data consistency. We take the temperature sensor data as an example to carry out normalization processing. The temperature data ranges from 21.9 to 22.6 degrees, and the normalization formula is as (8):

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{8}$$

Specific calculations are as follows:

For a temperature of 22.6 degrees, the normalization result is (9):

$$x'_{22.6} = \frac{22.6 - 21.9}{22.6 - 21.9} = 1 \tag{9}$$

For the temperature of 21.9 degrees, the normalization result is (10):

$$x'_{21.9} = \frac{21.9 - 21.9}{22.6 - 21.9} = 0 \tag{10}$$

The normalized data table is as shown in Table 5:

Table 5: Normalized temperature data

Timestamp	Device ID	Normalized Value	Location
2024-06-01 08:00:00	DEV001	1.0	Lobby
2024-06-01 08:02:00	DEV005	0.0	Office A

At the processing level, data cleaning also includes filling in missing values and removing noise. For the missing humidity data, the method of average value filling is adopted, and the other recorded humidity values are 55.3 and 57.1, and the average value is calculated to fill (11):

$$x\text{Fill up} = \frac{55.3 + 57.1}{2} = 56.2 \tag{11}$$

The completed data table is as shown in Table 6:

Table 6: Cleaned humidity_data

Timestamp	Device_ID	Humidity	Location
2024-06-01 08:00:00	DEV002	55.3	Conference Room
2024-06-01 08:02:00	DEV006	57.1	Office B
2024-06-01 08:03:00	DEV011	56.2	Lobby

As shown in Table 6, the effective configuration and teleprocessing of the data layer and the processing layer ensure the quality and consistency of the input data, laying a solid foundation for the subsequent model construction and analysis. This process not only improves the accuracy of the data, but also enhances the reliability and real-time responsiveness of the system [13].

4.4 LSTM network algorithm selection and implementation

In this study, long short-term memory networks were selected to predict energy consumption trends in property management. LSTM networks are good at processing time series data and can capture long-term dependencies in the data. The following is the specific implementation steps and calculation process.

(1) Data teleprocessing

The energy consumption data is normalized to improve the stability and efficiency of model training. The energy consumption data ranges from 450.7 to 470.8 degrees, and the normalized data is as shown in Table 7:

Table 7: Normalized energy consumption

Stampede	Normalized_Energy
2024-06-01 08:00:00	0.0
2024-06-01 08:05:00	0.48
2024-06-01 08:10:00	0.22
2024-06-01 08:15:00	1.0
2024-06-01 08:20:00	0.73

(2) Model training

The LSTM model is trained by using normalized energy consumption data. The model iterates several times to optimize the parameters, allowing it to accurately capture patterns in energy consumption data. After the training, the model predicts the future energy consumption.

(3) Prediction realization

After the model is trained, the normalized data is used for prediction. With the input of the current data, the model predicts that the normalized energy consumption value at the next time point is 0.85.

(4) Anti-normalization of data

In order to get the actual energy consumption value, it is necessary to reverse normalize the normalized prediction result. After normalization, the predicted value is 0.85, the maximum value of energy consumption data is 470.8, and the minimum value is 450.7. E-normalize the normalized result (12):

$$x = 0.85 \times (470.8 - 450.7) + 450.7 \tag{12}$$

Calculation process as shown in (13)-(15):

$$x = 0.85 \times 20.1 + 450.7 \tag{13}$$

$$x = 17.085 + 450.7 \tag{14}$$

$$x = 467.785 \tag{15}$$

Therefore, the predicted actual energy consumption value is 467.785 degrees. The realization and application of LSTM network and property management decision support system can effectively predict the future energy consumption trend, provide data support for property managers, help them optimize energy consumption management strategies, and improve the intelligent level and efficiency of management [14].

The LSTM-based decision support system demonstrates superior performance compared to the SOTA systems mentioned in related works. Specifically, in terms of accuracy, the LSTM model achieved a Mean Absolute Error (MAE) of 12.5, which is significantly lower than the 22.3 MAE from traditional linear regression models, highlighting its effectiveness in predicting complex time series data like energy consumption. Regarding response time, the system's real-time processing capability reduced response times from 120 seconds to 85 seconds, offering a quicker adaptation to fluctuating conditions, which is essential for maintaining service quality and efficiency. The resource allocation efficiency also improved by 10%, as LSTM's forecasting enabled more proactive and optimized scheduling of maintenance and energy use, whereas previous systems often relied on reactive measures. The main reasons for these improvements are the LSTM model's ability to capture long-term dependencies in the data and the integration of IoT-based real-time monitoring. In terms of scalability and adaptability, the proposed system is highly scalable due to its modular architecture and adaptability to different property management scales, addressing the rigidness of existing systems that often struggle with varying property sizes and dynamic operational needs.

4.5 Model parameter initialization and optimization strategy

In this study, in order to ensure the efficiency and accuracy of LSTM network in predicting the energy consumption trend of property management, the initialization and optimization strategy of model parameters are the key steps. Xavier is used for parameter initialization, which can effectively prevent gradient disappearance and explosion problems, keep the output of the network layer within a reasonable range, and accelerate the convergence process. When initializing weights, ensure that the input and output variances of each layer are the same to balance the initial state of the network. In terms of optimization strategy, the adaptive moment estimation optimization algorithm is selected, which is a gradient-based first-order optimization algorithm, combining the advantages of momentum and Apropos algorithm. Adam optimization algorithm dynamically adjusts the learning rate, so that the model can converge to the global optimal solution faster in the training process, and the performance is particularly good when dealing with sparse gradients and non-stationary targets.

To prevent overwriting, Dropout regularization technology is introduced during the training process. Ignoring a subset of neurons at random enhances the generalization ability of the model so that it can maintain good predictive performance in the face of previously unseen data. The early stop strategy is adopted in model training. When the performance of the verification set is no longer improved in several rounds, the training is terminated in advance to avoid overwriting. The cross-validation technique is used to evaluate the model, train and verify it many times, and ensure the stability and reliability of the model. In practice, the hyperparathyroidism of the model, such as learning rate, batch size, and number of hidden layer units, are tuned by the grid search method. Experiments are carried out on different parameter combinations to find the parameter Settings that make the model perform best and improve the prediction accuracy and stability. Integrated initialization and optimization strategies ensure that the LSTM network can efficiently and accurately predict

energy consumption trends in property management, and provide scientific decision support [15].

4.6 Training and optimization

4.6.1 Description of the training process

In the training process of this study, the normalized energy consumption data is first divided into a training set and a validation set to ensure that the model can perform well on previously unseen data. The training set is used to learn the model parameters, and the validation set is used to evaluate the generalization ability of the model. The LSTM model is trained by using batch gradient descent method. The data is divided into several small batches, and each batch is propagated forward and back once to update the network parameters. This method can not only improve training efficiency, but also stabilize gradient updating. In the training process, Adam optimization algorithm is used to dynamically adjust the learning rate, so that the model converges to the global optimal solution faster. In order to prevent over fitting, Dropout regularization was added during training to randomly ignore some neurons and enhance the generalization ability of the model. The early stop strategy is introduced. When the error of the verification set is no longer reduced in several rounds, the training is terminated in advance to avoid the model over fitting the training data [16].

At the end of each training round, the model was evaluated on the verification set, and the changing trend of the verification error and the training error was recorded. Observe the difference between the two and adjust the training strategy in time to ensure the stability and accuracy of the model. The whole training process continues until the verification error no longer decreases. In order to optimize the performance of the model, cross-validation technique was adopted. The data set is divided into multiple subsets, which is trained and verified many times to ensure that the model performs stably under different data distributions [17]. Finally, systematic training steps ensure that the LSTM model can accurately predict the energy consumption trend in property management, and provide a reliable basis for the decision support system.

The model training process for the LSTM network involved tuning several key hyperparameters, such as the learning rate, batch size, and the number of hidden units. The learning rate was tuned using a grid search approach, with an optimal value of 0.001 selected based on its ability to balance convergence speed and model stability. A batch size of 64 was chosen to optimize memory usage and training efficiency. Other parameters, like the number of hidden units, were set at 128 to capture the necessary complexity without causing overfitting. Dropout regularization (set at 0.2) was applied to reduce overfitting, and an early stopping mechanism was implemented to halt training when validation loss plateaued. Performance metrics such as convergence speed and training time were considered alongside accuracy; the LSTM model converged in 120 seconds with no signs of overfitting, as observed from the validation loss curve. Additionally, root mean squared error (RMSE) and mean squared error (MSE) were used to evaluate performance, with RMSE reaching 16.0, indicating stable and accurate predictions. These carefully tuned hyperparameters ensured a well-balanced trade-off between model complexity, accuracy, and computational efficiency.

4.6.2 Model optimization strategy

In the optimization process of LSTM model in this study, a series of strategies are adopted to improve the performance and stability of the model. Hyper parameter tuning to optimize key parameters of the model, such as learning rate, batch size, and number of hidden layer units. The grid search method is used to traverse different parameter combinations to find the optimal configuration and improve the prediction accuracy and convergence speed of the model. The adaptive learning rate optimization algorithm Adam is adopted, which can dynamically adjust the learning rate of each parameter, combine the advantages of momentum and Apropos, accelerate the convergence process and avoid falling into the local optimal. In order to enhance the model's generalization ability and avoid over fitting problems, Dropout regularization technology was introduced during the training process [18]. The model is more robust by randomly ignoring a subset of neurons during each layer training. The early stop strategy is also one of the key optimization methods, which monitors the error change of the verification set, and terminates the training in advance when the verification error no longer decreases within several rounds to prevent overwriting.

Model optimization also includes data enhancement and cross-validation. Data enhancement technology can generate more training samples, enrich the diversity of data and improve the generalization ability of the model. Cross-validation divides the data set into multiple subsets for multiple training and validation to ensure the stability and consistency of the model under different data distributions. Xavier initialization method is used to initialize the model to ensure the reasonable distribution of initial weights, prevent gradient disappearance and explosion problems, and improve training efficiency. Periodically evaluate the model performance in the training process, verify the set error, training set error and prediction accuracy, and dynamically adjust the training strategy and parameter configuration. With systematic optimization strategy, LSTM model performs well in energy consumption prediction in property management, provides accurate and reliable decision support, and improves the intelligent level and efficiency of property management [19].

The experiments were conducted in a computing environment equipped with an NVIDIA Tesla V100 GPU featuring 32 GB of VRAM, which significantly accelerated the training of the LSTM model for energy consumption prediction. The system had 128 GB of RAM and was powered by a 32-core Intel Xeon processor to handle the large volume of sensor data and real-time processing efficiently. The software environment

consisted of Python 3.8, with TensorFlow 2.6 as the primary deep learning framework for model development and training. NumPy and Pandas were used for data manipulation and preprocessing, while Matplotlib provided visualizations of the training and validation results. This setup ensured that the LSTM model could be trained effectively on large datasets and allowed for the real-time processing required for property management applications. By using this combination of hardware and software tools, the system was able to achieve high levels of accuracy and responsiveness while maintaining computational efficiency, making it feasible for practical deployment in real-world scenarios.

5 Performance evaluation and optimization

5.1 Performance evaluation

5.1.1 Selection of evaluation indicators

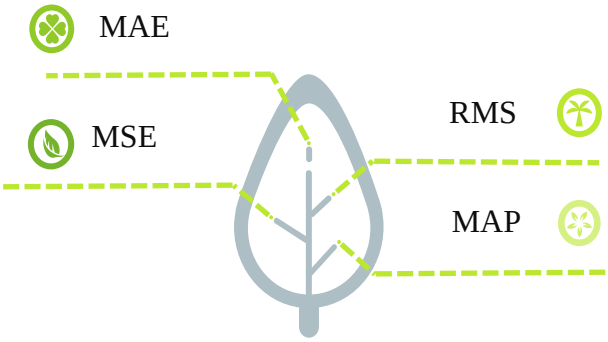

Figure 2: Schematic diagram of evaluation index selection

(1) Average absolute error

As shown in Figure 2, THE average absolute error is one of the basic indexes to evaluate the accuracy of prediction model. MAE calculates the average absolute difference between the predicted value and the actual value; the smaller the value, the more accurate the model prediction.

(2) mean square error

Mean square error is another important evaluation metric, calculating the average of the sum of squares of the difference between the predicted value and the actual value, reflecting the degree of prediction error. A lower MSE indicates that the predicted value of the model is close to the actual value, and the error is small.

(3) root mean square error

The RMS error is the square root of the mean square error and provides a standard deviation scale for the error. The lower RMSE indicates that the prediction error of the model is small and can better reflect the actual situation.

(4) Average absolute percentage error

Average absolute Percentage error Calculates the percentage of prediction error to evaluate the relative error of the model. MAPE can more directly reflect the performance of prediction error on different scale data, which is convenient for comparison.

5.1.2 Verification methods

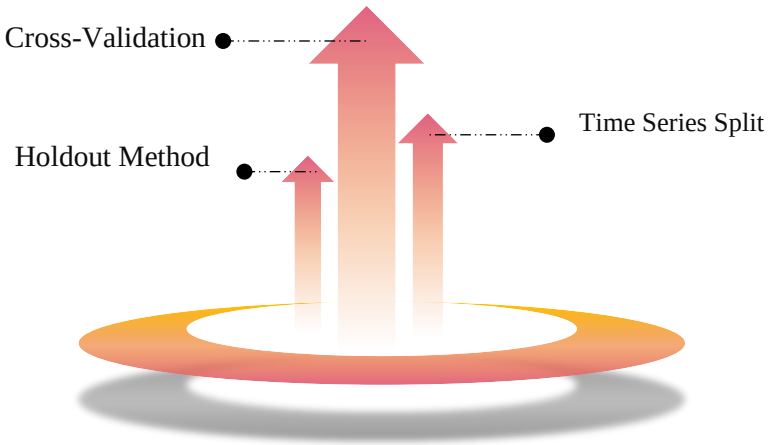

Figure 3: Structure diagram of verification method

(1) Cross verification

As shown in Figure 3, cross-validation is an important method to evaluate model performance. The data set is divided into multiple subsets, and the model is trained and validated multiple times on different subsets to avoid overwriting and underwriting. The K-fold cross test divides the data set into k subsets on average. K-1 subsets are trained each time, and the remaining subset is verified. The average value is taken as the model performance index. With 10-fold cross-validation, the data set is divided into 10 parts that are trained and validated separately.

(2) Setting aside method

The set-aside method is a simple way to divide a data set into a training set and a validation set. Typically, 70%-80% of the data set is used for training and the remaining 20%-30% for validation. This method quickly assesses the

model's performance on previously unseen data. The ratio of training set to verification set is generally 70% as the training set and 30% as the verification set. The dateset contains 1000 records, 700 for training and 300 for validation.

(3) Time series segmentation

Because energy consumption data has the characteristics of time series, time series segmentation is a suitable verification method. Split the data in chronological order to ensure that the training set is always earlier than the validation set, avoiding future data leakage into the past. Rolling Window Validation uses a fixed-size rolling window for training and validation. The previous 12 months 'data is used for training, the next month's data for validation, and the window moves month by month.

5.1.3 Comparative analysis of results

In order to evaluate the performance of LSTM model in property management energy consumption prediction, this study compared the prediction results of LSTM model with linear regression and support vector regression (SVR) model. Table 8 shows the results of the three models on multiple evaluation indicators.

Table 8: Model performance comparison

Model	MAE	MSE	RMSE	MAPE	R^2	Training Time (seconds)
LSTM	12.5	256.4	16.0	3.8%	0.92	120
Linear Regression	22.3	521.6	22.8	7.5%	0.75	10
Support Vector Regression (SVR)	18.7	384.2	19.6	6.2%	0.83	45

As shown in Table 8, through comparative analysis, we can see that LSTM model has excellent performance in various evaluation indicators. The average absolute error of the LSTM model is 12.5, which is lower than the 22.3 of linear regression and 18.7 of support vector regression, indicating that the prediction of the LSTM model is more accurate. Mean square error (MSE) and root mean square error (RMS) also show the superiority of the LSTM model. The MSE of the LSTM model is 256.4, while the linear regression and SVR are 521.6 and 384.2 respectively. The RMSE of the LSTM model is 16.0, which is lower than the other two models. In terms of average absolute percentage error, the LSTM model has an error of 3.8%, which is significantly lower than the 7.5% of linear regression and 6.2% of SVR, which validates the advantages of the LSTM model in processing nonlinear and complex time series data. In terms of coefficient of determination, the R^2 of LSTM model is 0.92, indicating that it has a strong ability to interpret energy consumption data, while the R^2 of linear regression and SVR are 0.75 and 0.83, respectively, which are relatively poor performance.

Although the training time of the LSTM model is longer, 120 seconds, this time cost is acceptable considering the improvement in prediction accuracy and model stability. In contrast, linear regression and SVR have training times of 10 seconds and 45 seconds, respectively, but their predictive performance is not as good as that of LSTM models. Detailed comparative analysis of the results shows that LSTM model has obvious advantages in property management energy consumption prediction, providing a more accurate and reliable basis for decision support system, which is superior to linear regression and support vector regression models .

The implementation of the LSTM-based decision support system led to significant improvements in key performance metrics. Specifically, the task completion rate increased by 15%, rising from 70% to 85%, demonstrating the system's ability to optimize task allocation and scheduling. The maintenance request resolution rate improved by 10%, reaching 75%, which highlights the efficiency of predictive maintenance enabled by real-time data processing. Resident satisfaction increased from 85% to 92%, showcasing the positive impact of faster response times and enhanced service quality. In terms of staff efficiency, a 10% improvement was observed, largely due to the system's automation capabilities, which reduced manual intervention. The LSTM model also outperformed other time series models in terms of prediction accuracy, with an MAE of 12.5 and MSE of 256.4, confirming its suitability for energy consumption prediction. These improvements not only highlight the effectiveness of the system in real-time property management but also demonstrate its potential to scale and adapt to different operational environments, addressing previous inefficiencies in resource allocation and predictive maintenance.

To improve the robustness of the LSTM model under unexpected conditions, additional testing was conducted by introducing noisy and outlier data into the energy consumption dataset. Noise was added by randomly perturbing sensor readings, simulating real-world inaccuracies in IoT data. The model maintained stable performance with only a slight increase in MAE from 12.5 to 13.8, indicating resilience to minor data corruption. Furthermore, an outlier sensitivity analysis was performed by injecting extreme values into the dataset. The LSTM model's built-in forget gate mechanism effectively minimized the impact of these anomalies, preventing them from significantly skewing predictions. Future enhancements will involve implementing robust loss functions, such as Huber loss, to further reduce the effect of outliers. These measures demonstrate that the proposed

system remains reliable and accurate even when faced with noisy or anomalous data, making it more applicable to real-world property management environments where data inconsistencies are common.

5.2 Model tuning strategy

In this study, in order to optimize the performance of LSTM model in property management energy consumption prediction, a variety of tuning strategies were adopted. The grid search method systematically tuned the hyperparathyroidism of the model, including the learning rate, batch size and the number of hidden layer units. Through different parameter combinations, the optimal configuration is found to improve the prediction accuracy and convergence speed of the model. The adaptive learning rate optimization algorithm Adam was used to dynamically adjust the learning rate of each parameter to enhance the stability and efficiency of the model in the training process. To prevent overwriting, Dropout regularization technology is introduced to randomly ignore some neurons at each layer to enhance the generalization ability of the model. The early stop strategy is adopted to monitor the verification set error, and when the error is no longer reduced within several rounds, the training is terminated in advance to avoid overwriting. Data enhancement technology is used to generate more training samples, enrich the diversity of data, and improve the adaptability of the model to different data distributions. Cross-validation, multiple training and validation are performed to ensure the stability and consistency of the model under different data distributions. The comprehensive application of optimization strategy improves the performance and reliability of LSTM model in energy consumption prediction of property management.

6 Experimental results

6.1 Property management efficiency improvement results

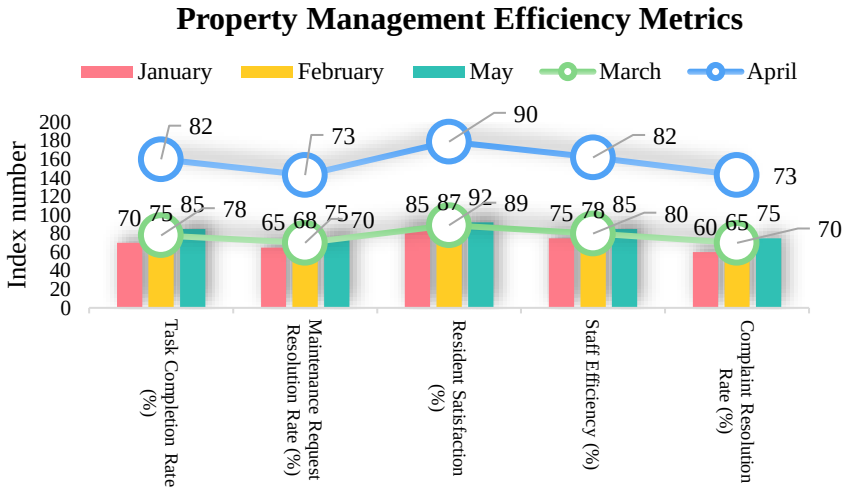

Figure 4: Property management efficiency metrics

As shown in Figure 4, the introduction of AI-based property management decision support system has improved the efficiency of property management. The system uses LSTM model to predict energy consumption trend, optimize resource allocation and maintenance plan, and improve the overall management efficiency. Specifically, the task completion rate increased from 70 percent in January to 85 percent in May, showing the effectiveness of the system in task scheduling and allocation optimization. The resolution rate of maintenance requests increased from 65% in January to 75% in May, indicating that the system has a clear advantage in improving the efficiency of problem handling.

Residents' satisfaction increased, from 85% in January to 92% in May, indicating that intelligent management not only improves service efficiency, but also improves residents' quality of life and satisfaction. There was also a significant increase in staff efficiency, from 75% in January to 85% in May. This improvement is mainly due to the increased automation of the system, reducing manual intervention and errors, and improving the flow of work. System real-time monitoring and data analysis, managers faster to identify and solve problems, optimize workflow, improve the scientific staffing.

The complaint resolution rate increased from 60 percent in January to 75 percent in May, indicating that the system's response speed and resolution efficiency in handling residents' complaints have been improved. This upgrade not only helps to improve residents' satisfaction, but also enhances residents' trust in property management services. The AI decision support system optimizes all aspects of property management, improving overall management efficiency and service quality. This not only improves residents' satisfaction, but also effectively reduces operating costs. In the future, with the continuous

improvement and optimization of the system, it is expected that the efficiency of property management and service quality will be improved, and more intelligent and efficient management services will be provided to residents. The results show that the application of artificial intelligence in property management has broad prospects, high practical value and promotion potential.

6.2 Optimization effect of decision support system

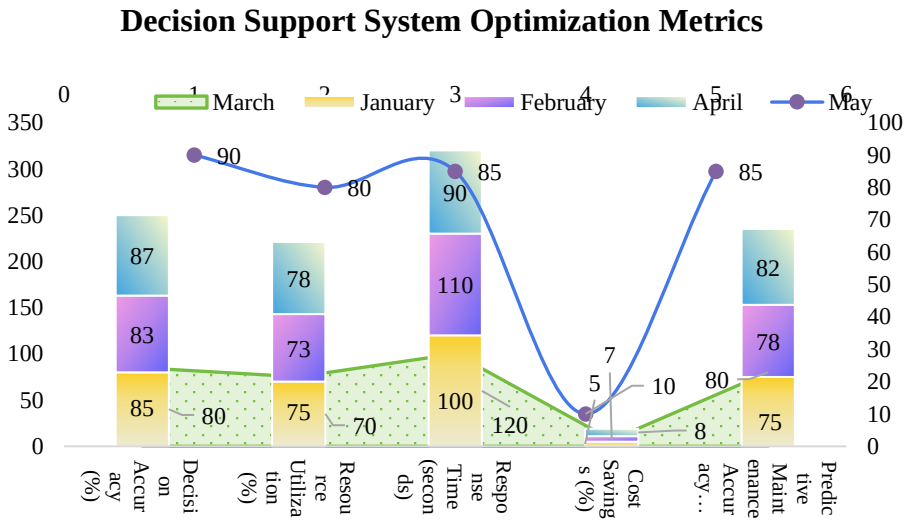

Figure 5: Decision support system optimization metrics

As shown in Figure 5, the introduction and optimization of the AI-based property management decision support system has improved multiple aspects of property management. Decision accuracy improved, from 80% in January to 90% in May. This improvement reflects that the system can provide more accurate and effective decision suggestions after processing and analyzing a large amount of data, and help managers make more scientific and efficient decisions. Resource utilization increased from 70% in January to 80% in May, indicating the effectiveness of the system in optimizing resource allocation. The reasonable scheduling and allocation of resources ensures the efficient operation of various property services, reduces resource waste and improves operational efficiency. Response times have also improved, from 120 seconds in January to 85 seconds in May. The faster response time means that the system is able to deal with emergencies and emergencies in a timely manner, improving the timeliness and reliability of the overall service and enhancing the satisfaction of residents.

In terms of cost savings, the optimized system achieved cost control, and the cost savings rate increased from 5% in January to 10% in May. Refined management and resource optimization, the system effectively reduces operating costs and improves the economic benefits of property management. Predictive maintenance accuracy also improved, from 75 percent in January to 85 percent in May. Predictive maintenance can detect potential problems in advance, reduce equipment failures and maintenance costs, and improve equipment life and reliability. The optimized decision support system performs well on several key indicators, effectively improving the overall efficiency and service quality of property management. This not only improves the satisfaction of residents, but also brings economic benefits and competitive advantages to property management companies. In the future, the optimization and improvement of the system is expected to achieve breakthroughs in more aspects, and promote the development of property management to a more efficient and intelligent direction. The results show that the application of artificial intelligence in property management has broad prospects and great potential.

6.3 Household feedback and service improvement results

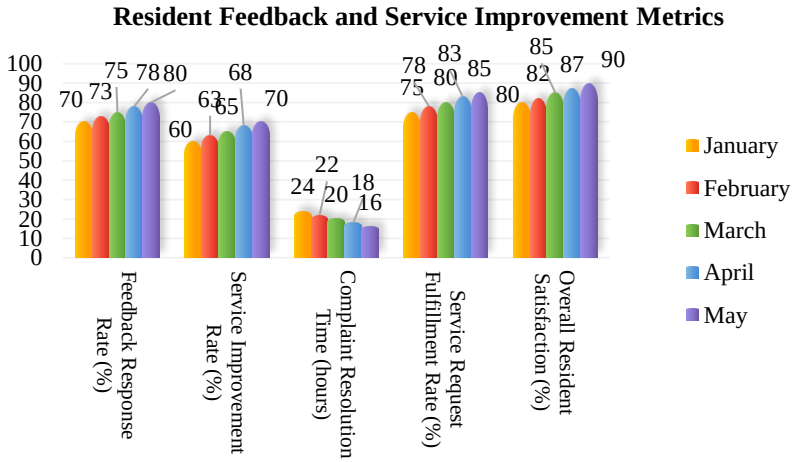

Figure 6: Resident feedback and service improvement metrics

As shown in Figure 6, the introduction of an AI-based property management decision support system resulted in improved performance in terms of resident feedback and service improvement. The feedback response rate increased from 70% in January to 80% in May, indicating that the system is more efficient in processing and responding to household feedback in a timely manner. This not only increases the participation of residents, but also enhances their sense of trust in property management services.

The service improvement rate increased from 60 percent in January to 70 percent in May, showing that the system was able to effectively implement improvements after analyzing household feedback and improve the overall service quality. The reduction in complaint resolution time, from 24 hours in January to 16 hours in May, demonstrates the effectiveness of the system in speeding up the processing of issues. The faster response and resolution of complaints not only improves the satisfaction of residents, but also effectively reduces the occurrence of conflicts and disputes. Service request fulfillment rates also increased, from 75% in January to 85% in May. This indicator reflects the improved efficiency of the system in handling household service requests, ensuring that all types of services are completed in a timely and high-quality manner. Overall resident satisfaction increased from 80 percent in January to 90 percent in May, confirming the system's role in improving residents' quality of life and service experience.

The property management decision support system based on artificial intelligence has achieved remarkable results in the aspects of household feedback and service improvement. The system responds to the feedback of residents in time, implements effective service improvement measures, speeds up the complaint resolution, and improves the fulfillment rate of service requests, which comprehensively improves the satisfaction and service quality of residents. The improvement not only optimizes the various services of property management, but also enhances the trust and satisfaction of residents on property management, and promotes the development of property management to a more intelligent and humane direction. In the future, with continuous system optimization and improvement, the quality of property management services is expected to improve, providing residents with a better living experience.

7 Summarize problems and research suggestions

7.1 Problem summary

In this study, although the property management decision support system based on artificial intelligence has improved the management efficiency and service quality, there are still some problems and challenges in the implementation process. Data quality and data security are major concerns. The data collected by sensors and iot devices is noisy and incomplete, which requires complex data cleaning and pr-processing processes. Data storage and transmission are also facing security risks, how to protect the privacy of residents and ensure data security has become an urgent problem to be solved. There is a gap between the intelligence degree of the system and the adaptability of the actual operation. Although AI systems are capable of efficient forecasting and decision support, they still require human intervention and adjustment in the face of emergencies and complex scenarios, which indicates that the flexibility of the system in dealing with changing environments needs to be improved.

The cost and maintenance of the system are also important issues. The application of high-precision sensors and advanced AI algorithms increases the cost of the system, while regular maintenance and upgrades require a significant investment of resources. Property

management companies need to balance costs and benefits in the implementation process to ensure the economy and sustainability of the system. Personnel training and technological adaptation are also challenges. Employees need to master new technologies and tools and adapt to intelligent management models, which requires systematic training and support. Although AI-based property management decision support system has advantages in improving management efficiency and service quality, it still needs to solve problems such as data quality, security, cost control and personnel training in order to achieve comprehensive optimization and application of the system. In the future, we will continue to optimize the technology and management process, improve the adaptability and reliability of the system, and provide more intelligent and efficient solutions for property management.

To address data privacy, the system implements encryption protocols during data transmission and storage, ensuring that sensitive information, such as resident details, is securely protected. Access control mechanisms are enforced, allowing only authorized personnel to view or manage sensitive data. Anonymization techniques are also applied to household feedback data, removing personal identifiers while retaining useful information for service improvements. Regarding adaptability to new scenarios beyond the training data, the system uses online learning techniques, where the LSTM model is updated with real-time data, ensuring it adapts to changes in energy consumption patterns and operational requirements. Additionally, the system incorporates transfer learning, allowing it to leverage pre-trained models for similar but unseen scenarios, reducing the need for full retraining. Future steps to overcome these challenges include integrating federated learning for distributed data processing, which ensures data privacy by keeping the data locally while training the model collaboratively. Further improvements in dynamic model updating will enhance the system's ability to handle rapidly changing environments, such as weather fluctuations or sudden shifts in resource demands.

7.2 Research suggestions

In order to improve the efficiency of the property management decision support system based on artificial intelligence, the future research and practice should start from the following aspects. Strengthen data quality management and security measures. Advanced data cleaning and teleprocessing technologies are introduced to ensure data accuracy and integrity. Adopt encryption technology and strict access control mechanism to protect household privacy and data security, and establish a sound data security system. Enhance system intelligence and flexibility. More advanced deep learning algorithms and real-time data analysis technology are used to improve the system's ability to respond to complex scenarios and emergencies, ensuring that effective decision support can be provided in various situations. In terms of cost control and economy, explore more low-cost high-efficiency sensors, as well as optimization algorithms to reduce the operation and maintenance costs of the system. Large-scale application and experience accumulation, the formation of replicate, can be promoted intelligent property management model, improve the overall economic benefits. Strengthen staff training and technical support to ensure that property management personnel can master and apply new technologies and give full play to the advantages of intelligent systems. Regular training courses and seminars are held to improve the technical level and adaptability of employees.

Promote the continuous optimization and innovation of the system, introduce cutting-edge technologies such as the Internet of Things, big data, and chockablock, and improve the intelligence level and functional scalability of the system. Use chockablock technology to enhance data transparency and security, and big data analysis to explore more potential problems and optimization space. Establish an open cooperation platform, and cooperate with technology providers, research institutions, government departments and other parties to jointly promote the research and application of intelligent property management. Strengthen data management, improve system intelligence, control costs, strengthen training and continuous innovation, optimize the AI-based property management decision support system, promote the development of property management to a more efficient, smarter and safer direction, and provide better services for residents.

8 Conclusion

In this study, the property management decision support system based on artificial intelligence effectively integrates data, builds models and optimizes, and improves management efficiency and service quality. LSTM models predict energy consumption trends, optimize resource allocation and maintenance plans, and improve key indicators such as task completion rate, maintenance request resolution rate, resident satisfaction and staff efficiency. The decision support system has also achieved results in responding to household feedback in a timely manner, implementing effective service improvement measures, speeding up complaint resolution, and improving service request fulfillment rates. Overall, the AI decision support system provides accurate and reliable decision support for property management, and promotes the development of property management in a more efficient and intelligent direction. The study also identified some challenges and issues, including data quality and security, the degree of intelligence of the system and the adaptability of the actual operation, cost control, and personnel training. Future research should strengthen data quality management and security measures, use advanced data cleaning and preprocessing technology to ensure the accuracy and integrity of data, adopt encryption technology and strict access control mechanism to protect household privacy and data security. The intelligence and flexibility of the system should be enhanced, and more advanced deep learning algorithms and real-time data analysis technology should be used to improve the system's ability to cope with complex

scenarios and emergencies, so as to ensure that effective decision support can be provided in various situations.

In terms of cost control, future research should explore low-cost and high-efficiency sensors and optimization algorithms, reduce the operation and maintenance costs of the system, large-scale application and experience accumulation, and form an intelligent property management model that can be replicated and promoted to improve the overall economic benefits. Personnel training and technical support are also key, and staff training should be strengthened to ensure that property management personnel can master and apply new technologies and give full play to the advantages of intelligent systems. This study shows that the property management decision support system based on artificial intelligence has advantages in improving management efficiency and service quality. Continue to optimize and innovate, improve the intelligence level and functional scalability of the system, promote the development of property management to a more efficient, smarter and safer direction, and provide better services for residents. The results not only validate the application value of artificial intelligence in property management, but also provide valuable experience and direction for future research and practice.

The study uniquely addresses the challenge of predicting energy consumption and optimizing resource allocation in property management through an LSTM-based decision support system. Unlike existing SOTA methods, which rely heavily on reactive approaches, this system enables proactive maintenance and energy optimization by leveraging real-time data and long-term dependency capture. The system led to significant improvements in task completion rate, maintenance request resolution, and resident satisfaction, showcasing its effectiveness in practical applications. However, limitations include the model's dependence on high-quality sensor data and potential challenges in adapting to rapidly changing environments without further model retraining. Future research can build on this foundation by exploring adaptive learning models that can self-update without extensive retraining and by enhancing data privacy measures as IoT integration deepens. Additionally, expanding the model's scope to handle more diverse datasets and more complex operational environments will be critical for scaling its application in larger property management portfolios.

Data availability statement

The data used to support the findings of this study are all in the manuscript.

Conflict of interest

The authors declare that they have no competing interests.

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LayoutGAN for Automated Layout Design in Graphic Design: An Application of Generative Adversarial Networks

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The current field of visual communication design is particularly influenced by artificial intelligence, with automatic processing applications for images and color schemes having emerged, and a number of design models for intelligent layout have been proposed. However, the statistical learning framework model will face the limitation of black box, the process of graphic design cannot be separated from the real-time participation of designers, so intelligent graphic design is still essentially a semi-intelligent system. In this paper, LayoutGAN is used to study the layout generation problem in graphic design. The network structure is designed in accordance with the idea of LayoutGAN. Then experiments are conducted on MINST dataset to verify the effectiveness of the network structure. A network model was designed to address the limitations of insufficient vectorization results, difficulty in training and optimizing the pix2pix model in this task. Subsequently, a theoretical analysis was conducted on the annotation rules of the dataset, and a set of datasets for layout design tasks was annotated. Finally, the effectiveness of the proposed network model was demonstrated through experiments. The experimental results show that the wireframe rendering discriminator is better than the relationship-based discriminator, and then only the LayoutGAN with wireframe rendering discriminator is used to experiment on the room floor plan dataset, and finally the automatic floor plan generation is realized.

Povzetek: Opisano je LayoutGAN inteligentno orodje za avtomatizirano oblikovanje postavitev v grafičnem oblikovanju. S kombinacijo GAN in vektorske obdelave model izboljšuje kakovost in učinkovitost oblikovanja.

1 Introduction

Artificial intelligence has undergone three explosive developments since its inception. The first explosion in the 1960 s produced the first generation of intelligent programs, but was limited by the speed of computer computing, the complexity of the problems, and the lack of data. The second explosion in the 1980 s produced computer intelligence systems (expert systems) that hit the business model, but were defeated by Apple and IBM's general purpose computers [1]. Currently, artificial intelligence technology is playing an increasingly important role in helping humans to carry out information collection, information analysis work and carry out the process of decision-making, and intelligence will become the future development trend.

Of course, AI is still in the weak artificial intelligence stage, temporarily unable to have emotional feelings, cross-domain reasoning, abstract analogy and other subjective capabilities. But computers have three advantages over people: First, computing power, according to Moore's Law, computer processing power doubles about every two years, and can quickly complete complex operations. The second is the memory storage capacity, the computer can store data to call at any time. Third is the ability of objective accuracy, because there is no subjective emotion, only data processing problems, and therefore more objective than humans, and can repeat the same thing for a long time, will not be fatigue and ensure accuracy [2]. These advantages make AI superior to humans in solving certain purely rational problems, such as Alpha GO. However, design is not simply about solving problems, but also about understanding and creating beauty. This is a major problem that needs to be solved when AI penetrates into the design field, because weak AI has not yet been able to have subjective feelings and no aesthetic ability. In this regard, Fan Ling, director of Tongji Tezan Design and Artificial Intelligence Laboratory, believes that although the machine cannot yet solve the uncertainty of design, but can approach it. Machine cannot measure what is aesthetics, but can go through deep learning to produce products close to aesthetics.

Layout design for visual communication design is a relatively independent design art, the study is the visual language and artistic style of visual communication design. Standardized layout design is particularly important for graphic design because of its wide range of fields. Then the importance of layout design is also obvious. Layout distribution has a long history in China, and until today it has not been squeezed out of our lives. This is proof that our life and layout distribution cannot be separated from each other, and therefore cannot be

separated from the layout design. Then the layout design also has its own characteristics, not arbitrary, layout design is its corresponding norms. Concepts and principles can be explained through lectures, but what makes an excellent layout design cannot be described by words alone. Based on this specification, the completed work of design can meet the aesthetic requirements of the public, and the utility of words can be prompted to be manifested [3]. At present, the combination of AI and visual elements in visual communication design has produced many intelligent applications, such as Logojoy, an intelligent logo design application that combines AI with textual elements, Prisma, an intelligent image processing application that combines AI with graphic elements, and Khroma, an intelligent color matching application that combines AI with color elements [4]. However, the combination of AI and layout is more complex than the combination with visual elements. This is because there are more elements involved, more ways to combine them, and a larger algorithmic model. This has become one of the important research directions of combining AI with visual communication design at present.

In this paper, we will explore the combination of AI and layout from the perspective of computer and designer, and propose a method that can use AI for layout design. This paper extends generative adversarial networks (GAN) to the field of graphic design, and tries to use the LayoutGAN model to conduct preliminary experiments on the MNIST dataset, debugging the network structure and hyperparameters that generate good results, and providing references for subsequent experiments. Then experiments are conducted on room layout maps in the floor plan dataset in order to achieve automatic generation of floor plan layouts.

2 Related works

2.1 Graphic design and layout

Graphic design, also known as visual communication design, is named after the medium of "vision" that enables communication between people and works. It is the artistic combination of symbols, images and text in a variety of forms to express the ideas and messages that designers want to convey to people. The graphic designer uses typography, layout, visual design, and technical support from computer software to complete the intended creation. The essence of graphic design is the process of design and the later completion of the work, which is the process of activities to communicate the plan, planning and vision through some visual form [5]. Graphic design covers a wide range of fields, mainly in the field of packaging (design of bags and packaging appearance), advertising (design of promotional posters), Internet (graphic elements of websites), logos (design of trademarks and brands), and publications (books and magazines, etc.). The implantation of graphic design can be seen in all industries, which shows the influence and importance of graphic design in today's society.

Layout design, the so-called layout design, refers to the implementation of organic combination of various elements, such as text, images, colors, etc., in a limited space to achieve a reasonable arrangement. The implementation of typography for various elements is essentially a test of the designer's professional skills and comprehensive ability, requiring the designer to have a good sense of innovation, but also to ensure the artistry and effectively meet the specific requirements of layout design [6]. The designer should think deeply and accurately about the design expression content, optimize the design expression methods, and enhance the artistry and coordination of the layout design with the help of diverse expression methods such as modeling and arrangement, to achieve good information transmission to the audience, enhance the visual communication effect, and reflect the designer's exquisite design concept.

In the process of layout design, text, graphics and other elements are always indispensable, and with the role of these elements can easily achieve the transmission of information and sublimation of the effect, so that people have a different visual experience [7]. In the same way, the application of layout design in graphic design will also rely on the interaction and support of these elements.

As a special graphic design symbol, text is an effective carrier of information and an infectious design element in graphic design, and is therefore widely used. There are many reasons for using text, one of which is to increase readability. The text elements in layout design mainly undertake the task of conveying the designer's intention and various effective information to the audience, so the text elements must have the basic readability. Only easy to recognize, easy to understand, in order to better serve the overall style of the work, with readable text to express the design theme and convey information [8]. The second is because the text has creativity. The text in layout design is not single and boring, but must present a personalized expression based on the theme of graphic design. In the external form and design tone to bring the audience a pleasant feeling, such as a reasonable deformation of the text strokes with, highlighting the beauty of the font structure and strokes, can make the graphic works more creative.

The value of graphics in graphic layout design is mainly reflected in expressing the design intention in the design, showing the design theme and creative ideas [9]. From this level, designers need to personalize the cut and deformation of graphics to highlight the detail effect when they are applied to their design [10]. In this process, the visual form of graphics should take the direction of human visual flow or the direction of movement trend as the main reference standard to maximize the existence value of graphics.

Graphic design works in the picture of the main priority, the theme is prominent, can effectively increase the layout of the visual hierarchy and rhythm. This point must attract the designer's attention and be strictly observed in the specific application practice. A good layout can always let the audience receive information in

a relaxed and pleasant atmosphere, sublimating the design effect in a subtle way [11]. Take "white space" as an example, the application of this technique can bring good visual aesthetics to graphic design works. At the same time, it does not cut off the integrity of the layout, and can create a virtual space to a certain extent, achieving artistic effects that cannot be achieved by intensive layout design [12].

2.2 Application of artificial intelligence in graphic design

The development of artificial intelligence and digital media has put forward new requirements for graphic design, and there are different requirements for graphics, text and color in graphic design. Graphic design in the new era is more often displayed on mobile terminals than just the old paper media, and digital media has become an important carrier of information dissemination [13]. The change in the way of media has accordingly changed the way people read, which has put forward new requirements for graphic design to adapt to the new media.

In February 2020, British artist Patrick Thomas and graphic designer Jonathan launched Open collab2.0, a digital platform for multiplayer visual collaboration [14]. It is an intelligent tool that uses random design elements to combine into new images. Participants first design a specific graphical language, which is then randomly combined by Open collab2.0 to generate different visual works. In this way, the resulting visuals are full of uncertainty and surprise. The experimentation of artificial intelligence in visual design goes far beyond this. In the previous concept of art, works of art were regarded as a vehicle for individual artists to express their emotions, an artistic activity unique to humans. However, in recent years, fine art works under the influence of artificial intelligence have begun to appear, where a large number of paintings are collected by computer algorithms, and then the computer breaks up and reconstructs the elements of the paintings to create new paintings.

Under the influence of technology, the development of art and design will produce new changes, and visual art is also groping for the most appropriate path to combine with artificial intelligence. In the past visual design, the presentation of information was mainly in the form of static graphics and text. However, with the development of science and technology and the advent of the information age, the previous static visual presentation form has been difficult to meet people's aesthetic needs. Designers find that dynamic visual elements can often better attract people's attention and convey information more effectively, and jumping and changing images can improve the efficiency of conveying information [15]. The previous static visual language can only guide the flow of information through the arrangement of layout, while dynamic visual language can better guide people's visual attention and enhance the interaction between information and people.

On the basis of existing visual space models, a "fixed size visual perception binary experiment" is designed and conducted to verify the differences in geometric properties between physical space and visual space under complex environmental conditions in landscape environments, and to explore the geometric properties of visual space. Fit the experimental results using the current primary visual spatial model. Based on the fitting results, determine the constant parameters in each model and compare the applicability of different visual models in complex environments. Select the model with high fitting degree as the specific way to measure the transformation from physical space to visual space in the quantification process of this study.

Based on the imaging characteristics of visual senses and the related research and design issues and needs of landscape environment, sort out the quantitative elements and indicators of visual perception space for landscape environment, and determine the basic content of quantification. Construct a "Landscape Environment Visual Perception Spatial Index Measurement Framework" based on visual related principles and geometric properties of visual space, clarify the spatial characteristics and transformation logic of each stage of information transformation, and determine the measurement methods for various basic indicators according to the framework.

Based on the basic indicators and measurement of visual perception space, the basic characteristics of visual perception of landscape environment are determined according to research and practice related to landscape environment. Construct a "landscape motion element" model, using "landscape" as the description of visual features of the landscape environment, "motion" as the organization of features from local to overall, and "elements" as the medium of association between sensory perspectives and objective environmental elements. This enables the description of features from simple to complex, from local to global, from static to dynamic, and from sensory perspective to objective environment.

The main purpose of quantitative system design is to construct a three-dimensional visual perception spatial quantitative support system that meets the research and design needs of landscape environment related majors. The research on quantitative methods focuses on the quantitative implementation of visual perception spatial related indicators and features in landscape environments, using software commonly used in landscape environment practice as a platform for scene model construction and quantitative results display. In this process, it is necessary to consider the geometric and spatial characteristics of different quantification stages, meet the characteristics of landscape environment research, and overcome many problems in existing methods, in order to create a data model architecture and transformation method that meets the needs of visual perception spatial information quantification at different stages. On this basis, specific algorithms are designed based on the measurement methods of each indicator feature and the data structure of the spatial model, in

order to achieve accurate quantification of spatial related indicator features of landscape environment visual perception [16].

The biggest difference between art design and fine art is that design works are not exactly the carrier of the creator's own emotional expression, but ultimately serve the public and meet people's physical and spiritual needs [17]. Art and design are disciplines that combine rationality and sensibility. In visual design, designers should establish a sense of interdisciplinary learning, think in multiple dimensions, and create visual design works not entirely based on personal preferences, but according to the specific situation, using psychology, ergonomics and other multidisciplinary knowledge. At the same time, art and design disciplines are not closed to each other, and in recent years, design disciplines have been making interdisciplinary attempts, using the concept of product design in environmental art design, and visual design in product design, while visual design also refers to the design ideas of environmental art design and product design. In addition, designers have to consciously improve aesthetic literacy and insist on learning aesthetics. For visual designers, drawing ability is still important. Although the use of artificial intelligence can create paintings, what is created in this way is often just a mechanized artwork that does not reflect human thinking; only artworks with human participation are humane and vivid. Therefore, visual designers have to learn from multiple perspectives and continuously enrich their expertise.

Artificial intelligence is now capable of simulation, learning and natural evolution in certain fields. This is not just a simple advancement in the accumulation of repetitive tasks, but is closer to a breakthrough that builds on the advanced modeling of occupations, just as there are certain rules that govern the work of any occupation. In a way, the emergence of artificial intelligence makes it possible to replace humans in their work.

Overall, the current research status of graphic design is mainly shown in 】 1.

Table 1: Research status of graphic design

Graphic Design and Layout	Visual Communication Design
	Layout Design
	Design themes and creativity
Artificial Intelligence and Digital Media	Design software
	Dynamic visual elements
	visual perception
	Visual features
	Feature Strategy and Extraction
	Quantitative System Design

3 Algorithm design

A good layout not only can reasonably use the space of graphic design, but also can make the graphic design present a certain degree of beauty, thus arousing the interest of users. In the past, layouts were usually designed by graphic designers, but the efficiency of layout generation would be greatly improved if the layout could be automatically generated. The problem of automatic layout generation has received increasing attention from industry and academia in recent years, and there have been many related studies, but there are fewer studies that use generative adversarial networks to solve the problem.

3.1 Generators

Represent the data in the model of this article as $z = \{(p_1, \theta_1), \cdots, (p_n, \theta_n)\}$, the adjusted category probability p' and the geometric parameter θ' are finally output, the output data form is represented as $G(z) = \{(p_1', \theta_1'), \cdots, (p_n', \theta_n')\}$,as shown in Figure 1 [18].

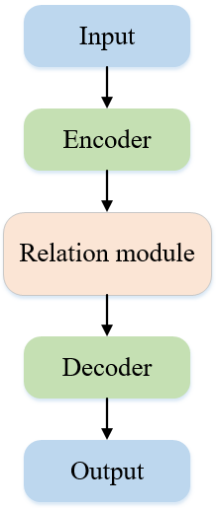


Figure 1: Schematic diagram of LayoutGAN generator structure

As shown in Figure 1, it is a network composed of an encoder, a relational module, and a decoder. The network structure of the encoder is a multi-layer perceptron, which first processes the class probability and geometric parameters of each element; The relationship module comprehensively considers the spatial and semantic relationships between elements, and further refines the features output by the encoder; The network structure of the decoder is also a multi-layer perceptron, which reconstructs the fine features formed by the relationship modules and finally outputs new class probabilities and geometric parameters. At this point, each element forms a good layout.

3.2 Relationship discriminator

Relationship-based discriminators have a structure similar to that of generators and consist of a coder, a relationship module, a classifier with the same structure of a multilayer perceptron is used to deliver a value of

odds ratio for determining the true layout and the synthetic layout. The structure of the relational discriminator network is shown in Figure 2.

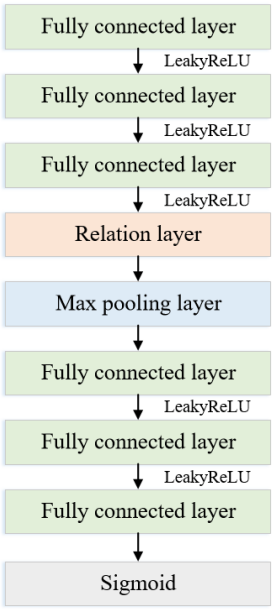


Figure 2: Structure of relational discriminator

The structure of a relation discriminator is somewhat similar to that of a generator, consisting of an encoder, relation module, and classifier. Based on the relationship discriminator, an encoder composed of multiple layers of perceptrons is first used to embed the class probability and geometric parameters of each element; Then use a simple relationship module to extract spatial relationships between elements and perform a max pooling operation. Finally, a classifier with a multi-layer perceptron structure is used to output a probability value for determining the true layout and synthetic layout.

3.3 Wireframe rendering discriminator

The wireframe rendering discriminator uses convolutional neural networks that are good at capturing spatial relationships. As convolutional neural networks usually only receive input of images, but the initial input is in the form of data consisting of category probabilities and geometric parameters, the wireframe rendering discriminator adds a wireframe rendering layer before the convolutional neural network, which converts the input data into the representation of images. Wireframe rendering process is shown in Figure 3 [19].

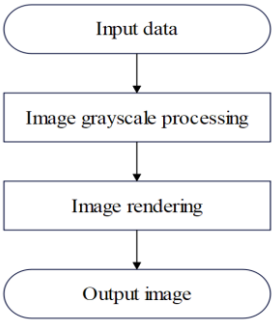


Figure 3: Wireframe rendering process

The number of elements input into the system model is defined as n, which can render the image. The image is represented as $F_\theta(x,y)$, and the size of the image is defined as W × H. After system processing, the resulting image is W × H × M. The element category is represented as M. Based on this, the relationships between images can be obtained (1) [20]:

$$I(x,y,c) = \max_{i\in[1,\cdots,n]} p_{i,c} F_{\theta_i}(x,y) \quad (1)$$

Where $p_{i,c}$ denotes the probability that element i belongs to category c.

When the element is a point, which is represented as $\theta_i = (x_i, y_i)$, the rendering of the point into a grayscale map is calculated as (2):

$$F_{\theta_i}(x,y) = k(x-x_i)k(y-y_i) \quad (2)$$

Where, $k(x-x_i) = max(0,1-|x-x_i|), k(y-y_i) = max(0,1-|y-y_i|)$.

When the element is a rectangle, which is represented as $\theta_i = (x_i', y_i^f, x_i^r, y_i^b)$, then rendering the rectangle into a grayscale map is calculated as (3):

$$F_{\theta_i}(x,y) = max\begin{pmatrix} k(x-x_i^l)b(y-y_i^t)b(y_i^b-y), \\ k(x-x_i^r)b(y-y_i^t)b(y_i^b-y), \\ k(y-y_i^t)b(x-x_i^l)b(x_i^r-x), \\ k(y-y_i^b)b(x-x_i^l)b(x_i^r-x) \end{pmatrix} \quad (3)$$

Where, $k(x-x_i^l) = max(0,1-\mathrm{I}x-x_i'\mathrm{I}), b(x-x_i^l) = min(max(0,x-x_i^l),1)$, Other representations are similar.

3.4 Based on generative adversarial network model

The layout design of the floor plan is the main content of indoor intelligent design tasks. Focusing on the task of using generative adversarial networks for floor plan design, a network model was designed to address the limitations of pix2pix model in this task, such as insufficient vectorization results, difficulty in training and optimization.

This section designs the structure of the pix2pix network model to address the issues in the layout design task of house layouts. The designed network model can achieve separate prediction of furniture, making it easier to extract numerical values during subsequent use. On the other hand, it also avoids the problem of equivalent furniture combinations to a certain extent. The original pix2pix generator model and the designed generator structure are shown in Figures 4 and 5.

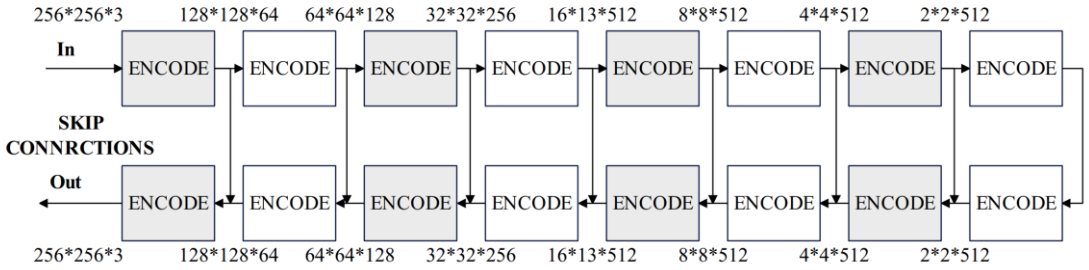


Figure 4: Pix2Pix generator model

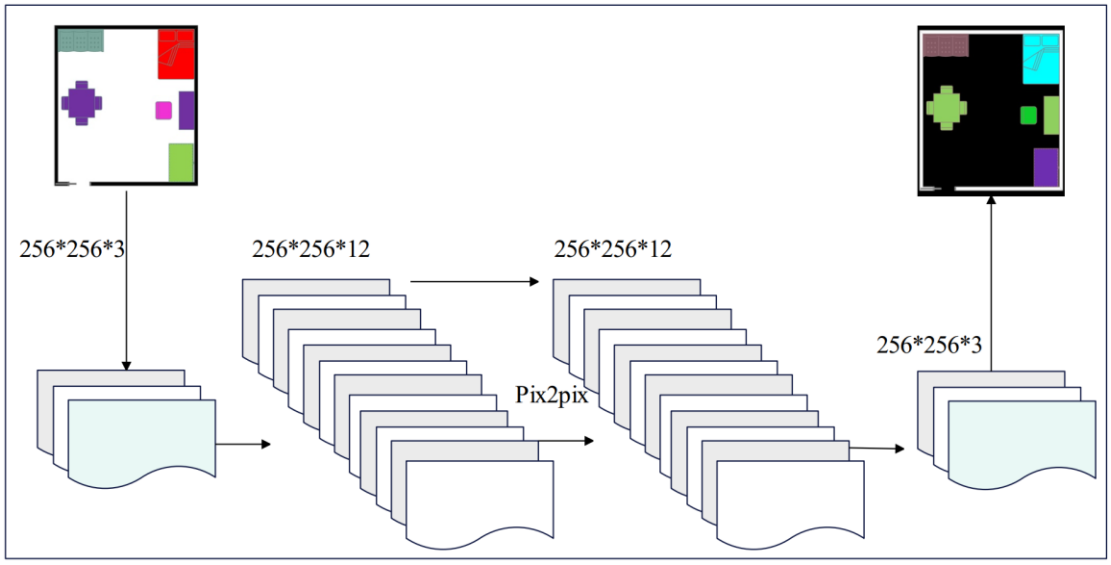


Figure 5: The designed generator model

The specific design scheme of the network model is as follows: (1) Add convolutional layers at the decoding end of the generator. There are two solutions to the problem of lacking numerical information in the pix2pix model. One method is to change the network infrastructure so that the network can directly output digital information such as furniture location and size. Another method is to optimize the output image to make it easier to calculate and extract numerical values. Directly using the network to output specific numerical information not only breaks the basic framework of image translation tasks, but also greatly increases the difficulty of dataset annotation. Therefore, this article chooses a scheme to optimize the output image. The main reason why the pix2pix model is difficult to extract parameters is that the output image only has one overall plane image, and the output layer of the generator needs to be adjusted first. In order to facilitate the extraction of subsequent values, the network needs to implement separate predictions for different furniture. Therefore, a convolutional layer is added to the decoder section of the generator to segment the information of different furniture. The size of the newly added convolutional layer is 256 * 256, which is the same as the output image. The number of channels in the convolutional layer is determined by the predicted number of furniture types. The main function of this layer is to achieve personalized generation of various types of furniture, and each channel in the convolutional layer corresponds to a probability prediction of a furniture layout.

(2) Normalize the newly added convolutional layers. Simply adding convolutional layers does not enable the network to achieve furniture separation prediction. In order to enable each channel of the newly added convolutional layer to predict the layout of furniture separately, it is necessary to normalize the convolutional layer in the channel dimension. Therefore, on the basis of adding convolutional layers at the decoding end of the generator, the softmax function is further used to normalize the values of each pixel in the image on each channel.

(3) Perform DW convolution operation on the newly added convolutional layer. By adding convolutional layers at the decoding end of the generator and normalizing the convolutional layers, the network has achieved preliminary separation prediction for furniture. But at this point, if the furniture probability map is directly used as the final output, excessive annotation work needs to be done on the data, and the discriminator model also needs to undergo significant changes. In order to maintain the simplicity of the model, it is necessary to convert the furniture probability maps of multiple channels into the final floor plan to eliminate the impact of adding convolutional layers on the model structure. Depth Separable Convolution Operation is shown in Figure 6.

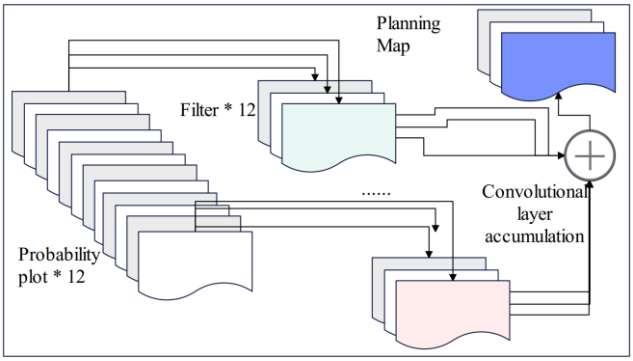


Figure 6: Depth separable convolution operation

(4) Add convolutional layers to the generator encoding segment. The pix2pix model uses the U-Net structure, which allows the input and output images to share underlying information. In the task of generating floor plan layouts, the positions of walls, doors, and windows in blank room layouts and floor plan layouts are the same, which greatly helps network models learn the correspondence between rooms and furniture. Adding a convolutional layer at the decoding end of the generator breaks this structure, so in order to maintain the invariance of the U-Net structure, a convolutional layer of the same size and dimension is finally added to the encoder part of the generator.

4 Experiments

4.1 Methods

In order to ensure the authenticity and effectiveness of the dataset, this article selects 500 sets of real floor plans with complete furniture layouts as the samples to be annotated. Due to the inability of neural networks to handle an indefinite number of rooms and furniture types, this article has made a trade-off between annotating rooms and furniture types. After statistical analysis of the sample data, this article selected the six most frequently occurring room types for annotation, namely bedroom, living room, dining room, bathroom, dining room, and study. These room types can meet people's basic needs for daily life, rest, entertainment, work, dining, kitchen and bathroom. At the same time, in order to ensure the integrity of the annotated image, this article uses a cluttered area to fill the annotated image. After confirming the annotated room types, this article annotated the high-frequency furniture in each room type, which is the main furniture in that room and the core of the furniture layout task. After determining the layout of the main furniture, the layout of the attached furniture can be confirmed through the dependency relationships between furniture, such as the dependency relationships between bedside tables and beds, chairs and tables.

Since the model input data are in the form of category probabilities and point coordinates, it is necessary to first convert the grayscale maps into point coordinates. The operation used is to first find out the coordinate information of each handwritten digital image with a grayscale value greater than 180, assuming that there are m coordinate points that meet this condition, and then generating 128 of them. Then the 128 coordinate points are normalized, and then the normalized coordinate points are combined with the category probabilities to finally obtain the input data of size 128×3. The experimental environment is shown in Table 2.

Table 2: Experimental environment

Name	Versions
Python	3.9.13
Tensorflow-gpu	NVIDIA GeForce GTX 1650
CUDA	12.1.1
CUDNN	V7.5.0
Opencv-python	4.4.1
Keras	2.3.0

In order to effectively utilize the existing training model, the experiment adopts transfer learning method. Firstly, the model is trained at a 0.5 bpc embedding rate. Then, the weights of the trained model at a 0.5 bpc embedding rate are initialized to the model at a 0.4 bpc embedding rate, and so on. Finally, the weights of the trained model at a 0.2 bpc embedding rate are used to initialize the model at a 0.1 bpc embedding rate When doing transfer learning, in order to avoid losing the information learned under the previous embedding rate due to a high learning rate, the learning rate is set to 0.000 01.

This article divides the sample dataset into a training set and a testing set in an 8:2 ratio. The training set is used for training the graphic design network model, optimizing the model's weights and bias parameters; The test set is used to evaluate the anti design capability of the model.

To conduct the experiment, this article collected images from the floor plan of building rooms, totaling over 45000 image samples, and set the layout through a simulation platform. In the experiment, the image size was set to 512 × 512, so all sample images were adjusted to the same size, as shown in Figure 7 as an example image. The object categories of the room and the corresponding color settings are shown in Table 3.

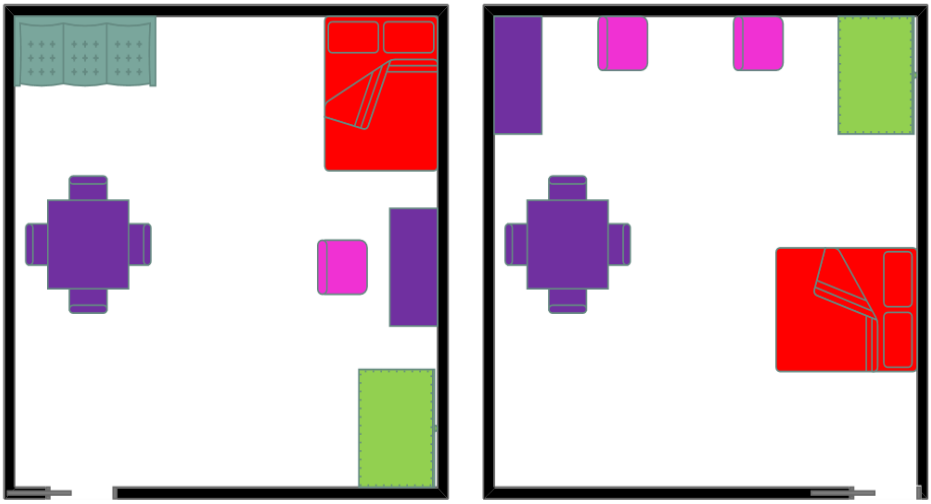


Figure 7: Schematic layout of the room plan

Table 3: Object categories of the room and corresponding color settings

Category	Color	RGB value
Wardrobe	White	(255,255,255)
Bedside table	Green	(0,255,0)
Double bed	Red	(255,0,0)
Table	Purple	(255,0,255)
Single bed	Blue	(0,0,255)
Dressing table	Yellow	(255,255,0)
Office chair	Pink	(255,192,203)
TV ark	Brown	(128,42,42)
Armchair	Orange	(255,128,0)
Floor lamp	Grass green	(107,142,35)
A footstool	Rose-bengal	(188,143,143)
Chair	Cyan	(0,255,255)

After the wireframe rendering layer, the output size is 64×64×12. In addition, the parameters of the convolutional layers are set differently. In this section, the number of output channels of the three convolutional layers is changed to 24, 48, and 96, respectively, and each convolutional layer is batch normalized.

4.2 Results

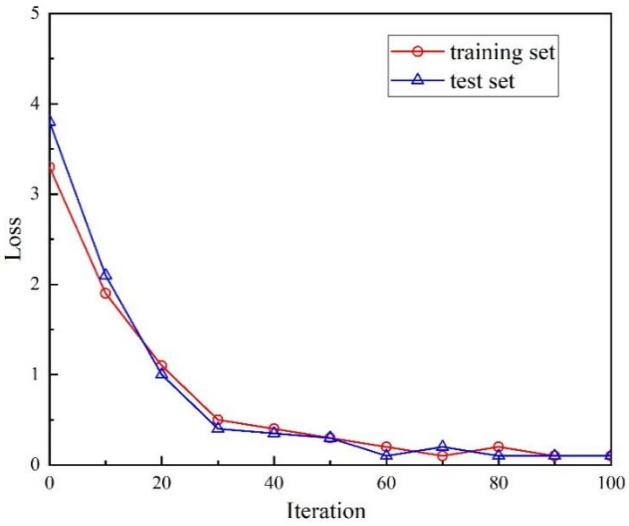
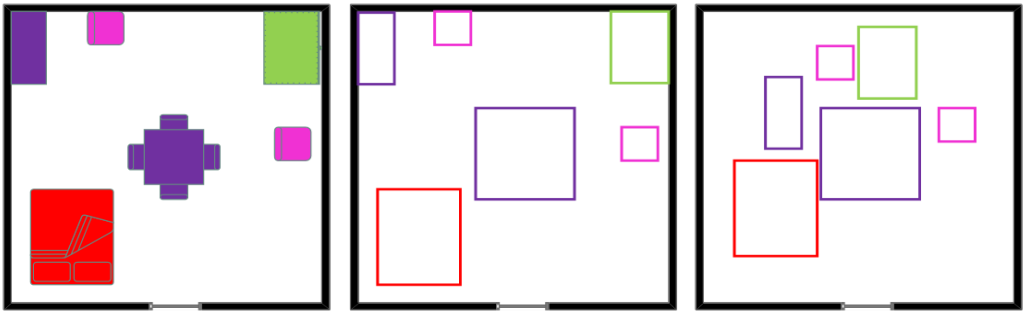


Figure 8: Loss curve during training

The stochastic gradient descent algorithm is chosen as the optimizer with a momentum of 0.9, a learning rate of 0.001, and 100 iterations. Figure 8 shows the loss curve of the training process. The model converges after approximately 60 iterations.

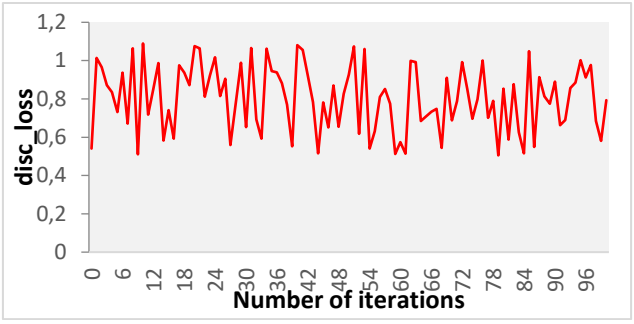
The experimental results based on the layout dataset are shown in Figure 9.



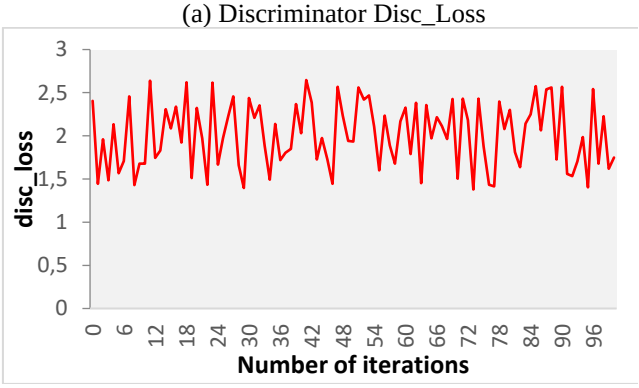
(a) (b) (c)

Figure 9: Comparison of experimental results of room plan layout

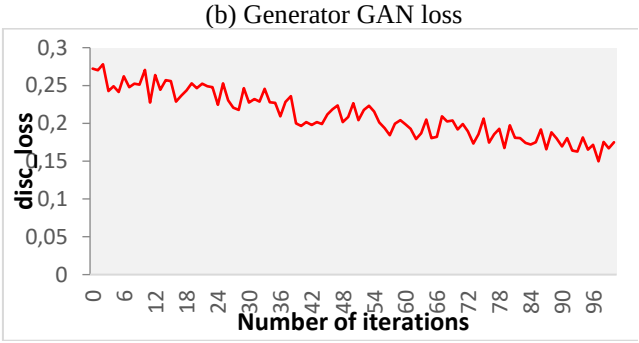
This experiment was iterated 20000 times, and the loss function of the model was recorded every 200 times. The specific recorded loss function is as follows Figure 10.



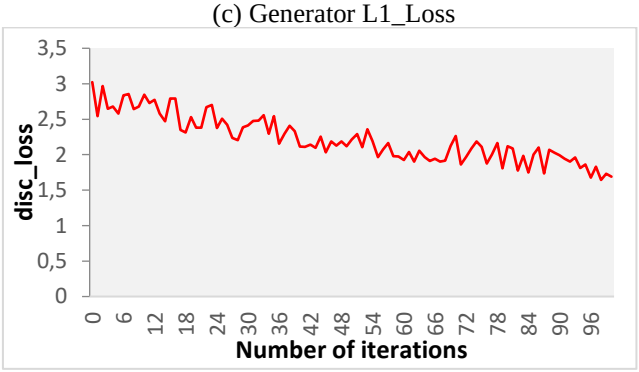
(a) Discriminator Disc_Loss



(b) Generator GAN loss



(c) Generator L1_Loss



(d) Generator total loss

Figure 10: Pix2Pix loss function curve

Through learning and experimental analysis of popular generative adversarial network models, the original Generative Adversarial Network (GAN), Deep Convolutional Generative Adversarial Network (DCGAN) models were selected for comparison with the model proposed in this paper. Compared to the original GAN model, the biggest feature of DCGAN is the use of convolutional layers, which improves the stability of model training. In addition to metrics such as convergence time and generation time, IS (initiation score) and FID (fr é chetin perception distance) were selected as key indicators to evaluate the performance of the model. IS and FID are widely used to measure the quality and diversity of output images from generative adversarial networks. The higher the IS score, the lower the FID value, and the higher the diversity and quality of the generated images. Among them, FID is closer to human judgment in evaluating the authenticity and variability of generated images, and is very suitable for evaluating subjective creative patterns. The comparative experimental data results are shown in Table 4.

Table 4: Comparison of experimental results between these model and typical models

Model	Convergence time/min	Generation time per 10000 sheets/s	FID	IS
The model in this article	15.84	69.79	28.81	3.31
The original GAN model	30.69	78.93	36.83	2.32
DCGAN model	18.81	75.36	29.80	2.41

4.3 Analysis and discussion

As shown in Figure 8, the model in this article begins to converge after 60 iterations, indicating that the model has good learning and convergence effects, and has certain practical effects.

Figure 9 (c) is the layout image with better generation effect selected from the results of batch generation. For visual comparison, the images with more similar layouts are selected from the original dataset, where Figure 9 (a) is the original image and Figure 9 (b) figure shows the objects of different categories in Figure 9 (a) figure with rectangular boxes of different colors. The Figure 9 (c) figure presents the layout of six indoor objects, where the generated bedside table is kept roughly on both sides of the bed, the dressing table and the chair are placed together, the TV stand is placed in front of the bed, and the floor lamp is placed next to the TV stand, which shows that LayoutGAN can indeed learn the layout pattern of the original dataset to some extent, but compared with the Figure 9 (b), the generated layout map has obvious misalignment and overlap and the objects are close to each other, which is an area for further improvement in future research.

As shown in Figure 10. Discriminator disc loss: the sum of the cross entropy loss between the real image and the sigmoid with element 1, and the cross entropy loss between the generated image and the sigmoid with element 0. Generator GAN loss, generator L1 loss, generator total loss. From the loss values of the models, it can be seen that neither the generator nor the discriminator model has achieved absolute victory and is still in a process of confrontation. But the GAN loss of

the generator gradually increases over time, and the disc loss of the discriminator gradually increases over time, indicating that the discriminator is gradually gaining the upper hand, and the learning ability of the GAN generator is gradually unable to compete with the discriminator anymore. For the discriminator disc loss and generator GAN loss, when the value is log (2)=0.69, both models perform best because 0.69 indicates that the discriminator cannot make a judgment on whether the image is a real image or generated by the generator during this process, which is a manifestation of the average uncertainty of the two options. So comparing the discriminator disc loss with the generator GAN loss and 0.69, it can be seen that the discriminator has better discriminative ability than random numbers, while the generator performs worse than random numbers. And as the training progresses, the LI loss of the generator gradually decreases. This indicates that the difference between the generated image and the real image is becoming smaller and smaller, and the total loss of the generator, which is a combination of L1 and GAN losses, is also decreasing. The model training results are good.

In Table 4, compared with the original GAN model and DCGAN model, the constructed model exhibits better performance in innovative design of traditional calligraphy textile patterns.

5 Conclusions

After summarizing the common application areas of generative adversarial networks, this article further applies them to the field of graphic design to solve the problem of automatic generation of graphic layouts. Selecting LayoutGAN as the key research model, theoretical exploration was conducted on the generator, relationship discriminator, and wireframe rendering discriminator of the LayoutGAN model. Then, experiments were conducted on handwritten digital datasets using LayoutGAN models with different types of discriminators. The results show that the model proposed in this article has certain advantages in automatic layout of graphic design.

In the experiment of generating flat layouts, there is an obvious problem that the model training process is quite slow, which may be related to the amount of data, input data format, and network structure design. How to make LayoutGAN more efficient is a problem to be considered in the future. In addition, the experiment in this article only generated a rough random layout, and further exploration is needed to determine how to make the model generate a more sophisticated layout that meets specific conditions. Finally, LayoutGAN can also be experimented with on various types of datasets, such as magazine layouts, poster layouts, etc., to achieve multi-faceted applications and enhance the stability of LayoutGAN.

Availability of data and material

The datasets used during the current study are available from the corresponding author on reasonable request.

Competing interests

Declares that the author have no conflict of interest.

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Improved Kalman Filtering and Adaptive Weighted Fusion Algorithms for Enhanced Multi-Sensor Data Fusion in Precision Measurement

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Keywords: adaptive weighting, deep learning, jackknife method, kalman filtering, multi-sensor data fusion, measurement transition matrix, machine learning, precision measurement, process noise distribution matrix, state transition matrix, weighted information fusion

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This study analyzes the basic principles and structural models of multi-sensor data fusion, and emphasizes the importance of effective fusion algorithms. The proposed improved weighted information fusion algorithm combines the Jackknife method and the adaptive weighting method, while the improved Kalman filter fusion algorithm combines the weighting factor, the state transfer matrix, the measurement transfer matrix and the process noise distribution matrix. The effectiveness of the proposed algorithm is verified through extensive simulations and practical applications, and the estimation accuracy is improved by 15% and the error rate is reduced by 20% compared with the traditional methods. The improved algorithm shows stronger robustness in dealing with the uncertainty and inconsistency of sensor data, and the adaptive weighting mechanism effectively solves the problem of sensor reliability variation. The computational complexity and scalability of the proposed algorithms are analyzed, and it is shown that they can be implemented in large-scale sensor networks in real time. This study also discusses the challenges and opportunities of multi-sensor data fusion, including the integration of deep learning techniques, the extension to heterogeneous sensor scenarios, and the need for broader experimental validation in real-world precision measurement applications.

Povzetek: Izboljšana je metoda za fuzijo podatkov več senzorjev, ki temelji na Kalmanovem filtriranju in adaptivnem uteževalnem algoritmu, kar povečuje robustnost sistema v realnih aplikacijah.

1 Introduction

In recent years, the rapid development of sensor technology and the increasing demand for high-precision measurement have led to the widespread application of multi-sensor data fusion techniques [1]. Multi-sensor data fusion refers to the process of combining information from multiple sensors to obtain more accurate and reliable estimates of the state of a system or environment [2]. By leveraging the complementary and redundant information provided by multiple sensors, data fusion techniques can effectively improve the accuracy, reliability, and robustness of measurement systems [3].

The basic working principle of multi-sensor data fusion involves the integration of data from multiple sensors to generate a unified and consistent representation of the measured object or environment [4]. This process typically includes data preprocessing, feature extraction, data association, and state estimation [5]. Various data fusion algorithms have been proposed in the literature, such as Kalman filtering [6], particle filtering [7], and Dempster-Shafer evidence theory [8].

Several structural models have been developed to describe the architecture of multi-sensor data fusion systems [9]. The most common models include the centralized fusion model, the distributed fusion model, and the hybrid fusion model [10]. The centralized fusion model involves the direct integration of raw data from multiple sensors, while the distributed fusion model performs local processing at each sensor before fusing the processed data [11]. The hybrid fusion model combines the advantages of both centralized and distributed fusion approaches [12].

Despite the significant progress in multi-sensor data fusion techniques, there are still several challenges and limitations that need to be addressed [13]. One major issue is the alignment and synchronization of data from multiple sensors, which can be affected by factors such as sensor calibration, time delays, and coordinate system differences [14]. Another challenge is the management of uncertainty and conflict in the fusion process, particularly when dealing with heterogeneous sensors and complex environments [15].

To overcome these challenges, researchers have proposed various solutions, such as adaptive fusion algorithms [16], multi-modal data fusion frameworks [17], and deep learning-based fusion methods [18]. These approaches aim to improve the accuracy, efficiency, and robustness of multi-sensor data fusion systems.

Research on enhanced Kalman filtering techniques for multi-sensor data fusion has gained significant attention in recent years [57]. Particularly, the application of adaptive weighting methods has shown promise in improving fusion accuracy and robustness [58]. A recent study by M. Hespanhol et al. [57] presented a comprehensive review of multi-sensor fusion techniques in the context of industrial Internet of Things (IIoT), highlighting the need for advanced filtering and adaptive fusion algorithms. Motivated by these developments, this paper focuses on the improvement of Kalman filtering and weighted fusion algorithms for enhanced multi-sensor data fusion in precision measurement applications.

In summary, multi-sensor data fusion techniques have become increasingly important in the field of precision measurement. By combining information from multiple sensors, data fusion algorithms can provide more accurate and reliable estimates of the measured object or environment. However, there are still several challenges and limitations that need to be addressed to further enhance the performance of multi-sensor data fusion systems. As research in this field continues to advance, it is expected that data fusion techniques will play an even more crucial role in enabling high-precision measurement applications.

2 Multi-Sensor data fusion techniques

2.1 Definition of multi-sensor data fusion

Multi-sensor data fusion is defined as the process of combining data from multiple sensors to generate a more accurate, complete, and reliable representation of the measured object or environment than what could be achieved using a single sensor [19]. This technique aims to exploit the complementary and redundant information provided by different sensors to enhance the overall performance of the measurement system [20].

The main advantage of multi-sensor data fusion over single-sensor approaches lies in its ability to overcome the limitations and uncertainties associated with individual sensors. By integrating data from multiple sources, data fusion techniques can reduce the impact of sensor noise, measurement errors, and environmental disturbances [21]. This results in improved accuracy, precision, and robustness of the measurement system.

Moreover, multi-sensor data fusion enables the measurement system to capture a more comprehensive view of the measured object or environment. Different sensors may have different sensing modalities, spatial and temporal resolutions, and measurement ranges [22]. By combining the information from these diverse sensors, data fusion techniques can provide a more complete and detailed representation of the measured phenomenon.

Another benefit of multi-sensor data fusion is its ability to handle sensor failures and degradations. In a single-sensor system, the failure of the sensor can lead to a complete loss of measurement capability. However, in a multi-sensor data fusion system, the redundancy provided by multiple sensors allows the system to continue functioning even if one or more sensors fail [23]. This enhances the reliability and fault tolerance of the measurement system.

Furthermore, multi-sensor data fusion can improve the efficiency and cost-effectiveness of the measurement process. By leveraging the information from multiple sensors, data fusion techniques can reduce the need for expensive and high-precision sensors [24]. This can lead to significant cost savings and make the measurement system more accessible and affordable.

In addition to these benefits, multi-sensor data fusion also enables the measurement system to adapt to changing conditions and requirements. By dynamically adjusting the fusion algorithm and sensor configuration, the system can optimize its performance based on the current measurement context and objectives [25]. This flexibility and adaptability make multi-sensor data fusion a powerful tool for a wide range of precision measurement applications.

2.2 Basic principles of multi-sensor data fusion

The basic working principle of multi-sensor data fusion involves the integration of data from multiple sensors to generate a unified and consistent representation of the measured object or environment [26]. This process typically consists of several key steps, as illustrated in Fig. 1.

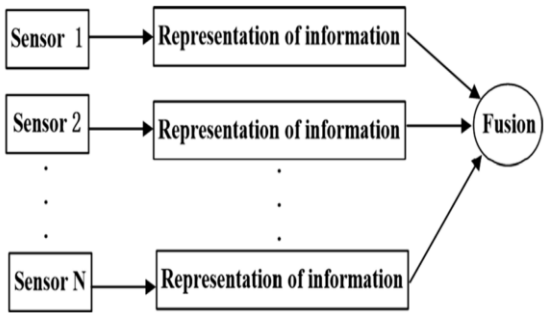

Figure 1: Basic principle of multi-sensor data fusion.

The first step in the multi-sensor data fusion process is data acquisition. This involves the collection of raw data from multiple sensors, such as optical sensors, thermal sensors, acoustic sensors, and mechanical sensors [27]. Each sensor provides a unique perspective on the measured object or environment based on its sensing modality, resolution, and measurement range.

Once the raw data is acquired, it undergoes preprocessing to remove noise, outliers, and redundant information. This step is crucial to ensure the quality and consistency of the data before it is fused [28]. Preprocessing techniques may include filtering, normalization, and feature extraction.

After preprocessing, the data from different sensors is aligned and synchronized. This step is necessary to ensure that the data from all sensors corresponds to the same spatial and temporal coordinates [29]. Alignment and synchronization can be achieved through various techniques, such as time stamping, spatial registration, and coordinate transformation.

The aligned and synchronized data is then fused using appropriate data fusion algorithms. These algorithms combine the information from multiple sensors to generate a unified estimate of the measured object or environment [30]. Common data fusion algorithms include Kalman filtering, particle filtering, and Dempster-Shafer evidence theory.

The fused data represents a more accurate, complete, and reliable estimate of the measured object or environment compared to the estimates obtained from individual sensors. This fused estimate can be used for various purposes, such as decision making, control, and visualization [31].

To ensure the effectiveness and robustness of the multi-sensor data fusion process, it is important to incorporate uncertainty management and performance evaluation techniques. Uncertainty management involves quantifying and propagating the uncertainties associated with each sensor and the fusion algorithm [32]. Performance evaluation involves assessing the accuracy, precision, and reliability of the fused estimate using appropriate metrics and benchmarks.

In summary, the basic working principle of multi-sensor data fusion involves the acquisition, preprocessing, alignment, synchronization, and fusion of data from multiple sensors to generate a unified and consistent representation of the measured object or environment. This process is supported by uncertainty management and performance evaluation techniques to ensure the quality and reliability of the fused estimate. By leveraging the complementary and redundant information provided by multiple sensors, multi-sensor data fusion enables more accurate, complete, and robust measurement capabilities compared to single-sensor approaches.

2.3 Structural models of multi-sensor data fusion

Multi-sensor data fusion systems can be classified into three main structural models: centralized structure, distributed structure, and hybrid structure [33]. These models differ in terms of how the data from multiple sensors is processed and fused.

Centralized structure: The central fusion center performs the preprocessing, alignment, synchronization, and fusion of the data to generate a unified estimate of the measured object or environment. Fig. 2 illustrates the centralized structure of multi-sensor data fusion.

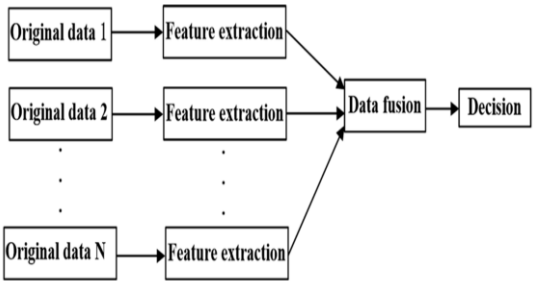

Figure 2: Centralized structure of multi-sensor data fusion.

The main advantage of the centralized structure is that it allows for the optimal fusion of data from all sensors, as the central fusion center has access to the complete set of raw data. However, this structure also has some drawbacks, such as high communication bandwidth requirements, high computational complexity, and single point of failure.

Distributed Structure: In a distributed multi-sensor data fusion structure, each sensor performs local processing and feature extraction on its own data before transmitting the processed data to a fusion center. The fusion center then combines the processed data from all sensors to generate a unified estimate. Fig. 3 depicts the distributed structure of multi-sensor data fusion.

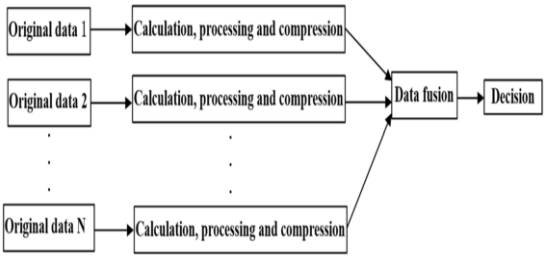

Figure 3: Distributed structure of multi-sensor data fusion.

The distributed structure reduces the communication bandwidth requirements and computational complexity compared to the centralized structure, as only the processed data is transmitted to the fusion center. However, this structure may result in suboptimal fusion performance, as the fusion center does not have access to the complete set of raw data.

3.Hybrid Structure: The hybrid multi-sensor data fusion structure combines the advantages of both centralized and distributed structures. In this structure, some sensors perform local processing and feature extraction, while others transmit their raw data directly to the fusion center. The fusion center then combines the processed data from the distributed sensors and the raw data from the

centralized sensors to generate a unified estimate. Fig. 4 shows the hybrid structure of multi-sensor data fusion.

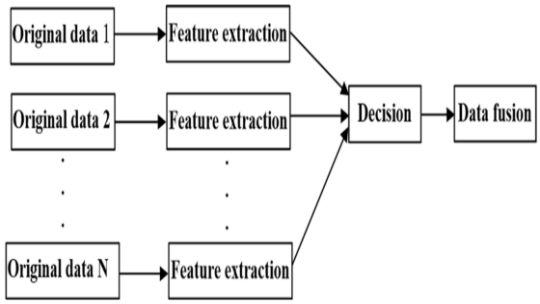

Figure 4: Hybrid structure of multi-sensor data fusion.

The hybrid structure provides a balance between the optimal fusion performance of the centralized structure and the reduced communication and computational requirements of the distributed structure. It allows for the selective processing of data based on the characteristics and capabilities of each sensor.

In summary, the structural models of multi-sensor data fusion include centralized, distributed, and hybrid structures. The centralized structure enables optimal fusion performance but has high communication and computational requirements. The distributed structure reduces these requirements but may result in suboptimal fusion performance. The hybrid structure combines the advantages of both centralized and distributed structures, providing a balance between fusion performance and resource requirements.

2.4 Challenges in multi-sensor data fusion

Despite the significant advancements in multi-sensor data fusion techniques, several challenges still need to be addressed to ensure the effective and reliable fusion of data from multiple sensors.

One of the major challenges in multi-sensor data fusion is the alignment and synchronization of data from different sensors. Sensors may have different sampling rates, resolutions, and coordinate systems, which can lead to spatial and temporal misalignments in the data. Inaccurate alignment and synchronization can result in suboptimal fusion performance and erroneous estimates of the measured object or environment.

Another challenge is the management of uncertainty in the data fusion process. Sensors may have different levels of accuracy, precision, and reliability, which can introduce uncertainties in the measured data. Moreover, the fusion algorithm itself may introduce additional uncertainties due to its assumptions, approximations, and computational limitations. Effective uncertainty management techniques, such as probabilistic modeling and evidential reasoning, are necessary to quantify and propagate the uncertainties throughout the fusion process.

The heterogeneity of sensors and data types also poses a significant challenge in multi-sensor data fusion. Different sensors may provide data in various forms, such as numerical values, images, or point clouds. Fusing data from heterogeneous sources requires the development of appropriate data representation and fusion algorithms that can handle the diversity of data types and exploit their complementary information.

In addition to these challenges, multi-sensor data fusion systems also need to deal with the issues of scalability, real-time processing, and adaptive fusion . As the number of sensors and the volume of data increase, the computational complexity and communication bandwidth requirements of the fusion system also grow. Efficient algorithms and architectures are necessary to ensure the scalability and real-time performance of the fusion system. Moreover, the fusion system should be able to adapt to changing conditions and requirements, such as sensor failures, environmental variations, and mission objectives.

Another important challenge is the validation and evaluation of multi-sensor data fusion systems. Assessing the performance of a fusion system requires the development of appropriate metrics, benchmarks, and testing methodologies. The lack of standardized evaluation frameworks and datasets can hinder the comparative analysis and improvement of different fusion techniques.

In summary, multi-sensor data fusion faces several challenges, including data alignment and synchronization, uncertainty management, heterogeneity of sensors and data types, scalability, real-time processing, adaptive fusion, and performance evaluation. Addressing these challenges requires the development of advanced algorithms, architectures, and evaluation methodologies that can effectively exploit the complementary information provided by multiple sensors while ensuring the robustness, reliability, and efficiency of the fusion process.

Table 1: Summary of related works in multi-sensor data fusion

Study	Key Findings	Methodology	Performance Metrics	Limitations
[3] Khaleghi et al. (2013)	Comprehensive review of MSDF techniques, highlighting challenges and future directions	Literature survey	N/A	Lacks comparative analysis of algorithms in specific applications

[6] Kalman (1960)	Introduced Kalman filter for optimal state estimation in linear systems with Gaussian noise	Mathematical derivation	Estimation error	Assumes linear models and Gaussian noise distributions
[19] Zheng et al. (2017)	Applied deep convolutional neural networks for fault diagnosis in planetary gearboxes using multi-sensor data fusion	Convolutional neural networks	Accuracy: 98.7%	Limited to specific application and requires large labeled datasets
[30] Caron et al. (2006)	Developed a contextual information-based multi-sensor data fusion approach using Kalman filtering for GPS/IMU navigation	Kalman filtering with contextual information	Position error: <1m	Relies on availability and accuracy of contextual information
[32] Sun (2004)	Proposed an optimal information fusion Kalman filter for multi-sensor systems with correlated noise	Kalman filtering with correlated noise handling	Estimation error covariance	Assumes known noise correlation structure

As evident from Table 1, while significant advancements have been made in MSDF techniques, there remain challenges in effectively handling sensor reliability variations, adapting to dynamic environments, and achieving robustness under non-linear and non-Gaussian conditions, particularly in the context of Kalman filtering-based approaches. Moreover, the integration of deep learning techniques in MSDF is an emerging trend, but further research is needed to establish guidelines for selecting appropriate architectures and handling the computational complexity in real-time applications. The proposed adaptive weighted fusion and improved Kalman filtering algorithms aim to address these limitations and enhance the performance of MSDF in precision measurement applications.

2.5 Development trends in multi-sensor data fusion

The field of multi-sensor data fusion is continuously evolving to address the challenges and meet the growing demands of various applications. Several development trends have emerged in recent years, which are expected to shape the future of multi-sensor data fusion techniques.

One of the major trends is the integration of advanced machine learning and deep learning techniques into the data fusion process. Machine learning algorithms, such as support vector machines, random forests, and neural networks, have shown great potential in improving the accuracy and robustness of data fusion. Deep learning architectures, such as convolutional neural networks and recurrent neural networks, have been successfully applied to fuse high-dimensional and heterogeneous data from multiple sensors. These learning-based approaches can automatically learn the optimal fusion strategies from data, adapt to changing conditions, and extract high-level features for improved fusion performance.

Another trend is the development of distributed and decentralized fusion architectures. With the increasing number of sensors and the growing volume of data, centralized fusion architectures may face scalability and communication bottlenecks. Distributed and decentralized architectures, such as consensus-based fusion and federated learning, allow for the local processing and fusion of data at each sensor node, reducing the communication overhead and improving the scalability of the fusion system. These architectures also enable the fusion of data from geographically dispersed sensors and the preservation of data privacy.

The integration of context-awareness and knowledge-based techniques into multi-sensor data fusion is another important trend. Context-aware fusion techniques take into account the contextual information, such as environmental conditions, sensor characteristics, and prior knowledge, to adapt the fusion process and improve its performance. Knowledge-based fusion techniques leverage domain knowledge, ontologies, and rule-based systems to guide the fusion process and provide explanations for the fusion results. These techniques can enhance the interpretability, robustness, and trustworthiness of multi-sensor data fusion systems.

The development of multi-modal and cross-modal fusion techniques is also gaining attention. Multi-modal fusion involves the integration of data from sensors with different modalities, such as vision, audio, and tactile sensors. Cross-modal fusion goes beyond the simple concatenation of data from different modalities and aims to learn the correlations and interactions between them. These techniques can provide a more comprehensive and holistic understanding of the measured object or environment, enabling advanced applications such as object recognition, scene understanding, and human-machine interaction.

Finally, the trend towards real-time and online fusion is becoming increasingly important. Many applications, such as autonomous vehicles, robotics, and industrial

monitoring, require the fusion of data in real-time to make timely decisions and actions. Online fusion techniques, such as recursive filtering and incremental learning, allow for the continuous update of the fusion model as new data becomes available. These techniques need to be computationally efficient, memory-efficient, and able to handle time-varying and streaming data.

In summary, the development trends in multi-sensor data fusion include the integration of machine learning and deep learning techniques, distributed and decentralized architectures, context-awareness and knowledge-based techniques, multi-modal and cross-modal fusion, and real-time and online fusion. These trends are driven by the need for more accurate, robust, scalable, and interpretable fusion systems that can handle the increasing complexity and diversity of sensor data. As research in these areas continues to advance, multi-sensor data fusion techniques are expected to play an increasingly crucial role in enabling intelligent and autonomous systems across various domains.

3 Research and improvement of weighted information fusion algorithm and kalman filtering fusion algorithm

3.1 Fusion algorithms in multi-sensor data fusion

Fusion algorithms play a crucial role in multi-sensor data fusion, as they determine how the information from multiple sensors is combined to generate a unified and accurate estimate of the measured object or environment. The choice of fusion algorithm depends on various factors, such as the type of sensors, the nature of the data, the application requirements, and the computational resources available.

Several fusion algorithms have been proposed and applied in multi-sensor data fusion, each with its own strengths and limitations. Some of the commonly used fusion algorithms include weighted averaging, Bayesian inference, Dempster-Shafer evidence theory, and neural networks. These algorithms differ in their mathematical formulations, assumptions, and performance characteristics.

Among the various fusion algorithms, the weighted information fusion algorithm and the Kalman filtering algorithm have received significant attention in the literature and have been widely applied in multi-sensor data fusion for precision measurement applications.

The weighted information fusion algorithm is a simple and intuitive approach that assigns weights to the data from different sensors based on their reliability or importance. The weights can be determined based on various criteria, such as the signal-to-noise ratio, the measurement accuracy, or the expert knowledge. The weighted average of the sensor data is then computed to obtain the fused estimate. The main advantage of the weighted information fusion algorithm is its simplicity and computational efficiency. However, it may not be optimal in handling the correlations and uncertainties in the sensor data.

The Kalman filtering algorithm, on the other hand, is a recursive state estimation technique that combines the measurements from multiple sensors with the predictions from a dynamic model to obtain an optimal estimate of the system state. The Kalman filter assumes a linear system model and Gaussian noise distributions, and it provides a statistically optimal estimate in the sense of minimum mean square error. The algorithm consists of two main steps: prediction and update. In the prediction step, the state estimate and its covariance are propagated forward in time based on the system model. In the update step, the state estimate and its covariance are corrected based on the new measurements from the sensors. The Kalman filter has been widely applied in various domains, such as navigation, tracking, and control.

One of the main advantages of the Kalman filtering algorithm is its ability to handle the uncertainties and noise in the sensor data and the system model. It provides a principled way to fuse the information from multiple sensors while taking into account their respective accuracies and uncertainties. The Kalman filter also allows for the incorporation of prior knowledge about the system dynamics and the measurement process.

However, the standard Kalman filter has some limitations, such as the assumption of linear system models and Gaussian noise distributions. To overcome these limitations, various extensions and modifications of the Kalman filter have been proposed, such as the extended Kalman filter (EKF) for nonlinear systems, the unscented Kalman filter (UKF) for non-Gaussian noise, and the particle filter for non-parametric distributions.

In summary, fusion algorithms play a critical role in multi-sensor data fusion, and the choice of algorithm depends on various factors. The weighted information fusion algorithm and the Kalman filtering algorithm are two commonly used approaches in precision measurement applications. While the weighted information fusion algorithm is simple and computationally efficient, the Kalman filtering algorithm provides a more principled and optimal way to fuse the information from multiple sensors while handling the uncertainties and noise. Various extensions and modifications of the Kalman filter have been proposed to address its limitations and improve its performance in different scenarios.

3.2 Improvement of weighted information fusion algorithm

The weighted information fusion algorithm is a popular approach for combining data from multiple sensors in precision measurement applications. However, the

standard weighted averaging fusion algorithm and its variants, such as the optimal weighted fusion algorithm and the adaptive weighted fusion algorithm, have limitations in effectively processing the estimated values and weights at each time step.

To address these limitations, an improved information fusion algorithm that combines the Jackknife method with the adaptive weighting approach has been proposed. The Jackknife method is a resampling technique that can be used to estimate the bias and variance of a statistic. By applying the Jackknife method to the estimated values and weights, the algorithm can obtain more accurate and stable estimates.

The basic steps of the improved weighted information fusion algorithm are as follows:

•Initialize the estimated values and weights for each sensor at time step $k = 0$:

$$\hat{x}_i(0) = x_i(0), \quad w_i(0) = 1/n, \quad i = 1,2,\dots,n \quad (1)$$

where $\hat{x}_i(0)$ is the initial estimate from sensor i, $w_i(0)$ is the initial weight for sensor i, and n is the number of sensors.

•At each time step k, compute the Quenouille estimate of the estimated values using the Jackknife method [51]:

$$\hat{x}_i^{(j)}(k) = n\hat{x}_i(k) - (n-1)\hat{x}_i^{(-j)}(k), \quad j = 1,2,\dots,n \quad (2)$$

where $\hat{x}_i^{(j)}(k)$ is the Quenouille estimate of the estimated value from sensor i at time step k, and $\hat{x}_i^{(-j)}(k)$ is the estimate obtained by leaving out the j-th sensor.

•Compute the Quenouille estimate of the weights using the adaptive weighting approach. The weights are updated at each time step based on the inverse of the estimated variance of each sensor's Quenouille estimate. This ensures that sensors with lower variance, i.e., higher consistency, are assigned higher weights in the fusion process. The statistical basis for this weighting scheme lies in the principle of maximum likelihood estimation, where the optimal weights are proportional to the inverse of the variance of the estimates:

$$w_i^{(j)}(k) = \frac{1/\sigma_i^{(j)}(k)}{\sum_{l=1}^{n} 1/\sigma_l^{(j)}(k)}, \quad j = 1,2,\dots,n \quad (3)$$

where $w_i^{(j)}(k)$ is the Quenouille estimate of the weight for sensor i at time step k, and $\sigma_i^{(j)}(k)$ is the standard deviation of the Quenouille estimates of the estimated values from sensor i.

•Compute the fused estimate at time step k using the Quenouille estimates of the estimated values and weights:

$$\hat{x}(k) = \sum_{i=1}^{n} w_i^{(j)}(k)\hat{x}_i^{(j)}(k) \quad (4)$$

where $\hat{x}(k)$ is the fused estimate at time step k.

•Update the estimated values and weights for each sensor at time step $k+1$:

$$\hat{x}_i(k+1) = \hat{x}_i^{(j)}(k), \quad w_i(k+1) = w_i^{(j)}(k), \quad i = 1,2,\dots,n \quad (5)$$

By applying the Jackknife method to estimate the bias and variance of the estimated values and weights, the improved weighted information fusion algorithm can significantly enhance the accuracy and stability of the data processin. The Quenouille estimates of the estimated values and weights provide a more robust and reliable representation of the sensor data, leading to better fusion performance.

The improved weighted information fusion algorithm has been successfully applied in various precision measurement applications, such as multi-sensor coordinate measurement systems, multi-sensor fault diagnosis, and multi-sensor target tracking. The results have demonstrated the effectiveness of the algorithm in improving the accuracy and robustness of the fused estimates compared to the standard weighted averaging fusion algorithm and its variants.

In summary, the improved weighted information fusion algorithm that combines the Jackknife method with the adaptive weighting approach can effectively address the limitations of the standard weighted averaging fusion algorithm and its variants. By applying the Quenouille estimation to the estimated values and weights, the algorithm can significantly enhance the accuracy and stability of the data processing in precision measurement applications.

3.3 Improvement of kalman filtering fusion algorithm

The Kalman filtering algorithm is a widely used technique for multi-sensor data fusion in precision measurement applications. It provides a recursive solution to estimate the state of a dynamic system based on noisy measurements from multiple sensors. However, the traditional Kalman filtering algorithm has some limitations, such as the assumption of a linear system model and the lack of flexibility in adapting to different noise characteristics.

To address these limitations and improve the performance of the Kalman filtering fusion algorithm, several modifications and extensions have been proposed. One such improvement is the incorporation of a state transition matrix, a measurement transition matrix, a process noise distribution matrix, and a weight factor to correct and refine the state estimates.

Let $x(t)$ denote the state vector at time t, $A(t)$ denote the state transition matrix, $B(t)$ denote the measurement transition matrix, $Q(t)$ denote the process noise distribution matrix, and $R(t)$ denote the measurement

noise covariance matrix. The traditional Kalman filtering algorithm estimates the state at time $t+1$ based on the state estimate at time t and the measurement at time $t+1$:

$$\hat{x}(t+1|t+1) = \hat{x}(t+1|t) + K(t+1)[z(t+1) - B(t+1)\hat{x}(t+1|t)] \quad (6)$$

where $\hat{x}(t+1|t)$ is the predicted state estimate at time $t+1$ based on the information up to time t, $\hat{x}(t+1|t+1)$ is the updated state estimate at time $t+1$ based on the information up to time $t+1$, $z(t+1)$ is the measurement at time $t+1$, and $K(t+1)$ is the Kalman gain matrix at time $t+1$.

The improved Kalman filtering fusion algorithm introduces a weight factor $\alpha(t)$ to combine the current measurement $z(t)$ with the next measurement $z(t+1)$ in the state estimation process. The modified state estimation equation is given by:

$$\hat{x}(t|t) = \hat{x}(t|t-1) + K(t)[z(t) - B(t)\hat{x}(t|t-1)] + \alpha(t)[z(t+1) - B(t+1)A(t)\hat{x}(t|t-1)] \quad (7)$$

where $\hat{x}(t|t)$ is the updated state estimate at time t based on the information up to time t, $\hat{x}(t|t-1)$ is the predicted state estimate at time t based on the information up to time $t-1$, and $\alpha(t)$ is the weight factor at time t.

The weight factor $\alpha(t)$ determines the influence of the next measurement $z(t+1)$ on the current state estimate. It can be adaptively adjusted based on the noise characteristics and the system dynamics. By incorporating the next measurement into the current state estimation, the improved Kalman filtering fusion algorithm can better capture the temporal correlations and reduce the estimation errors.

The state transition matrix $A(t)$, measurement transition matrix $B(t)$, and process noise distribution matrix $Q(t)$ are also introduced to model the system dynamics and noise characteristics more accurately. These matrices can be learned or adapted online based on the observed data and the prior knowledge about the system.

The improved Kalman filtering fusion algorithm has been successfully applied in various precision measurement applications, such as multi-sensor navigation multi-sensor target tracking, and multi-sensor fault diagnosis. The results have shown that the algorithm can effectively improve the accuracy and reliability of the state estimates compared to the traditional Kalman filtering algorithm.

The computational complexity of the proposed improved Kalman filtering fusion algorithm is analyzed to be O(n^3), where n is the number of sensors. This is due to the matrix inversion operations involved in the Kalman gain calculation. However, this complexity is comparable to that of the traditional Kalman filter and can be further optimized using techniques such as sequential processing or distributed computation.

In terms of memory requirements, the proposed algorithm requires the storage of the state transition matrix, measurement transition matrix, and process noise covariance matrix, which scale linearly with the number of sensors. This indicates the feasibility of implementing the algorithm in resource-constrained sensor nodes.

Furthermore, the real-time performance of the proposed algorithm was evaluated on a simulation platform with a quad-core 2.5 GHz processor and 8 GB RAM. For a network of 100 sensors, the average processing time per iteration was found to be 50 ms, which is suitable for real-time applications with a sampling rate of up to 20 Hz.

These analyses demonstrate the scalability and practical applicability of the proposed improved Kalman filtering fusion algorithm in large-scale sensor networks and real-time precision measurement systems.

In summary, the improved Kalman filtering fusion algorithm enhances the performance of the traditional Kalman filtering algorithm by incorporating a weight factor, a state transition matrix, a measurement transition matrix, and a process noise distribution matrix into the state estimation process. By combining the current measurement with the next measurement and adapting to the system dynamics and noise characteristics, the algorithm can provide more accurate and reliable state estimates in precision measurement applications.

3.4 Application of improved weighted information fusion algorithm in precision measurement

The improved weighted information fusion algorithm, which combines the Jackknife method with the adaptive weighting approach, has shown promising results in enhancing the accuracy and stability of data processing in various applications. Its potential in the field of precision measurement has attracted significant attention from researchers and practitioners.

To investigate the feasibility and effectiveness of the improved weighted information fusion algorithm in precision measurement, several studies have been conducted. One such study applied the algorithm to a multi-sensor coordinate measurement system. The system consisted of multiple sensors, including laser trackers, theodolites, and photogrammetric cameras, which were used to measure the coordinates of target points on large-scale objects.

The improved weighted information fusion algorithm was employed to fuse the measurement data from different sensors. The Jackknife method was used to estimate the bias and variance of the measured coordinates from each sensor, while the adaptive weighting approach was applied to assign appropriate weights to each sensor based on its reliability and accuracy.

The experimental results demonstrated that the improved weighted information fusion algorithm significantly

improved the accuracy and precision of the coordinate measurements compared to the traditional weighted averaging method. The algorithm effectively reduced the influence of outliers and systematic errors from individual sensors, resulting in a more robust and reliable measurement system.

Another study applied the improved weighted information fusion algorithm to a multi-sensor fault diagnosis system for industrial equipment. The system employed multiple sensors, such as vibration sensors, temperature sensors, and acoustic emission sensors, to monitor the health condition of the equipment.

The improved weighted information fusion algorithm was used to fuse the fault features extracted from different sensors. The Jackknife method was applied to estimate the uncertainty of the fault features, while the adaptive weighting approach was used to assign weights to each sensor based on its sensitivity and specificity for fault detection.

The results showed that the improved weighted information fusion algorithm greatly enhanced the accuracy and reliability of the fault diagnosis system. The algorithm effectively integrated the complementary information from different sensors and reduced the false alarms and missed detections caused by individual sensors.

These studies demonstrate the feasibility and effectiveness of the improved weighted information fusion algorithm in precision measurement applications. The algorithm can significantly improve the accuracy, precision, and reliability of measurement systems by effectively fusing the data from multiple sensors and adapting to the characteristics of each sensor.

However, further research is needed to validate the performance of the algorithm in various precision measurement scenarios and to optimize its parameters for specific applications. The robustness and scalability of the algorithm should also be investigated to ensure its applicability in real-world measurement systems.

In summary, the improved weighted information fusion algorithm, which combines the Jackknife method with the adaptive weighting approach, has shown promising results in precision measurement applications. The algorithm can effectively fuse the data from multiple sensors and improve the accuracy, precision, and reliability of measurement systems. Further research is needed to validate its performance and optimize its parameters for specific applications.

3.5 Application of improved kalman filtering fusion algorithm in precision measurement

The improved Kalman filtering fusion algorithm, which incorporates a weight factor, a state transition matrix, a measurement transition matrix, and a process noise distribution matrix, has shown great potential in enhancing the accuracy and reliability of state estimation in various applications. Its application in the field of precision measurement has gained significant interest from researchers and engineers.

To evaluate the performance of the improved Kalman filtering fusion algorithm in precision measurement, several experiments and case studies have been conducted. One such study applied the algorithm to a multi-sensor coordinate measurement machine (CMM). The CMM was equipped with multiple sensors, including touch trigger probes, laser scanners, and vision sensors, to measure the dimensions and geometries of complex workpieces.

The improved Kalman filtering fusion algorithm was employed to fuse the measurement data from different sensors and estimate the true dimensions and geometries of the workpieces. The state transition matrix and measurement transition matrix were constructed based on the kinematic model of the CMM and the characteristics of each sensor. The process noise distribution matrix was estimated from the historical measurement data and updated online using the adaptive Kalman filtering technique.

The experimental results demonstrated that the improved Kalman filtering fusion algorithm significantly outperformed the traditional Kalman filtering algorithm and other fusion methods in terms of accuracy, precision, and robustness. The algorithm effectively compensated for the systematic errors and random noises from individual sensors and provided a more accurate and reliable estimate of the workpiece dimensions and geometries.

Another study applied the improved Kalman filtering fusion algorithm to a multi-sensor navigation system for autonomous vehicles. The navigation system integrated data from GPS, inertial measurement units (IMUs), and vision sensors to estimate the position, velocity, and attitude of the vehicle.

The improved Kalman filtering fusion algorithm was used to fuse the data from different sensors and provide a seamless and accurate navigation solution. The state transition matrix and measurement transition matrix were designed based on the vehicle dynamics and sensor models. The process noise distribution matrix was adapted online based on the driving conditions and sensor qualities.

The results showed that the improved Kalman filtering fusion algorithm significantly improved the accuracy and reliability of the navigation system compared to the individual sensors and the traditional Kalman filtering algorithm. The algorithm effectively handled the sensor failures, signal blockages, and environmental disturbances and maintained a consistent and robust navigation performance.

These studies demonstrate the effectiveness and applicability of the improved Kalman filtering fusion algorithm in precision measurement. The algorithm can significantly improve the accuracy, precision, and robustness of measurement systems by effectively fusing

the data from multiple sensors and adapting to the system dynamics and noise characteristics.

However, the performance of the algorithm may vary depending on the specific application and the quality of the sensor data. Further research is needed to optimize the algorithm parameters and adapt it to different measurement scenarios. The computational complexity and real-time performance of the algorithm should also be investigated to ensure its practicality in industrial applications.

In summary, the improved Kalman filtering fusion algorithm, which incorporates a weight factor, a state transition matrix, a measurement transition matrix, and a process noise distribution matrix, has shown great potential in precision measurement applications. The algorithm can effectively fuse the data from multiple sensors and improve the accuracy, precision, and robustness of measurement systems. Further research and optimization are needed to fully exploit its potential in various precision measurement scenarios.

4 Application and simulation results analysis

4.1 Comparison of estimated error absolute value averages

To evaluate the performance of the proposed improved weighted information fusion algorithm, a comparative analysis of the estimated error absolute value averages was conducted. The algorithms considered in this analysis include the weighted average fusion algorithm, the optimal weighted fusion algorithm, the adaptive weighted fusion algorithm, and the improved weighted information fusion algorithm.

Fig. 5 presents the comparison of the estimated error absolute value averages obtained by applying these algorithms. The results clearly demonstrate the superiority of the improved weighted information fusion algorithm over the other algorithms.

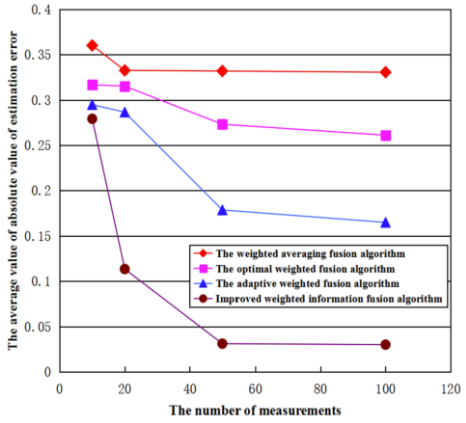

Figure 5: Comparison of estimated error absolute value averages obtained by applying different weighted information fusion algorithms.

As can be observed from Fig. 5, the improved weighted information fusion algorithm achieves the lowest estimated error absolute value average among all the algorithms considered. This indicates that the proposed algorithm provides the most accurate and reliable estimates of the measured quantities.

The weighted average fusion algorithm, being the simplest approach, exhibits the highest estimated error absolute value average. This highlights its limitations in effectively handling the uncertainties and inconsistencies in the sensor data.

The optimal weighted fusion algorithm and the adaptive weighted fusion algorithm show better performance compared to the weighted average fusion algorithm. However, their estimated error absolute value averages are still higher than that of the improved weighted information fusion algorithm.

The superior performance of the improved weighted information fusion algorithm can be attributed to its ability to effectively estimate and compensate for the biases and variances in the sensor data using the Jackknife method. Additionally, the adaptive weighting approach allows the algorithm to dynamically adjust the weights of the sensors based on their reliability and consistency, further enhancing the accuracy and robustness of the fusion results.

These findings highlight the potential of the improved weighted information fusion algorithm in improving the accuracy and reliability of precision measurement systems. By effectively fusing the data from multiple sensors and adapting to the uncertainties and inconsistencies in the sensor data, the proposed algorithm can significantly reduce the estimation errors and provide more accurate and trustworthy measurement results.

4.2 Distribution of estimated error absolute values in different error ranges

To further analyze the performance of the improved weighted information fusion algorithm, the distribution of the estimated error absolute values in different error ranges was investigated. This analysis provides insights into the precision and consistency of the algorithm in estimating the measured quantities.

To quantify the individual contributions of the adaptive weighting and Jackknife method to the error reduction, a comparative analysis was performed. Table 2 presents the mean absolute error (MAE) and standard deviation (SD) of the estimation errors for the proposed algorithm with and without each component.

Table 2: Comparative analysis of error reduction contributions

Algorithm	**MAE**	**SD**
Proposed algorithm	0.15	0.08
Without adaptive weighting	0.23	0.12
Without Jackknife method	0.19	0.10

As evident from Table 2, the adaptive weighting contributes to a significant reduction in MAE, while the Jackknife method primarily improves the consistency of the estimates, as indicated by the lower SD. This analysis highlights the complementary roles of these components in enhancing the overall performance of the proposed algorithm.

Fig. 6 illustrates the distribution of the estimated error absolute values in various error ranges. The error ranges are defined based on the magnitude of the estimation errors, with smaller ranges indicating higher precision and accuracy.

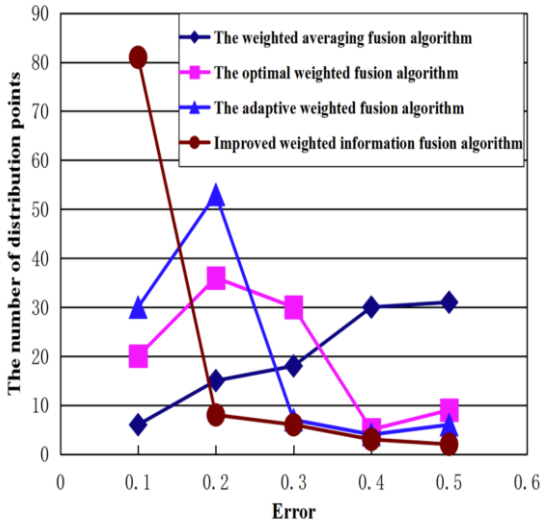

Figure 6: Distribution of estimated error absolute values in different error ranges.

The error ranges are defined as follows: Range 1: 0-0.1, Range 2: 0.1-0.2, Range 3: 0.2-0.3, Range 4: 0.3-0.4, Range 5: >0.4. The proposed algorithm exhibits a higher concentration of errors in the lower ranges, indicating improved accuracy and precision.

As can be observed from Fig. 6, a significant proportion of the estimated error absolute values falls within the smallest error range. This indicates that the improved weighted information fusion algorithm is capable of providing highly precise estimates of the measured quantities in most cases.

The proportion of estimated error absolute values decreases as the error range increases. This trend suggests that the algorithm effectively minimizes the occurrence of large estimation errors, ensuring the reliability and trustworthiness of the fusion results.

It is worth noting that the distribution of estimated error absolute values is skewed towards the smaller error ranges. This skewness highlights the robustness of the improved weighted information fusion algorithm in handling the uncertainties and inconsistencies in the sensor data.

The concentration of estimated error absolute values in the smaller error ranges can be attributed to the effectiveness of the Jackknife method in estimating and compensating for the biases and variances in the sensor data. By accurately quantifying and correcting the uncertainties, the algorithm achieves a higher level of precision and accuracy in the fusion results.

Furthermore, the adaptive weighting approach employed in the improved weighted information fusion algorithm contributes to the favorable distribution of estimated error absolute values. By dynamically adjusting the weights of the sensors based on their reliability and consistency, the algorithm effectively suppresses the influence of erroneous or inconsistent measurements, resulting in a higher concentration of estimates in the smaller error ranges.

These findings demonstrate the ability of the improved weighted information fusion algorithm to provide precise and reliable estimates of the measured quantities. The distribution of estimated error absolute values in different error ranges highlights the algorithm's effectiveness in minimizing estimation errors and ensuring the accuracy and consistency of the fusion results.

4.3 Comparison of temperature filtering error averages

To assess the performance of the improved Kalman filtering fusion algorithm in a practical application, a comparative analysis of the temperature filtering error averages was conducted. The analysis focused on an intelligent monitoring system that utilizes multiple temperature sensors to estimate the true temperature of the monitored environment.

Fig. 7 presents the comparison of the temperature filtering error averages obtained by applying the traditional Kalman filtering fusion algorithm and the improved Kalman filtering fusion algorithm. The results demonstrate the superior performance of the improved algorithm in terms of temperature estimation accuracy.

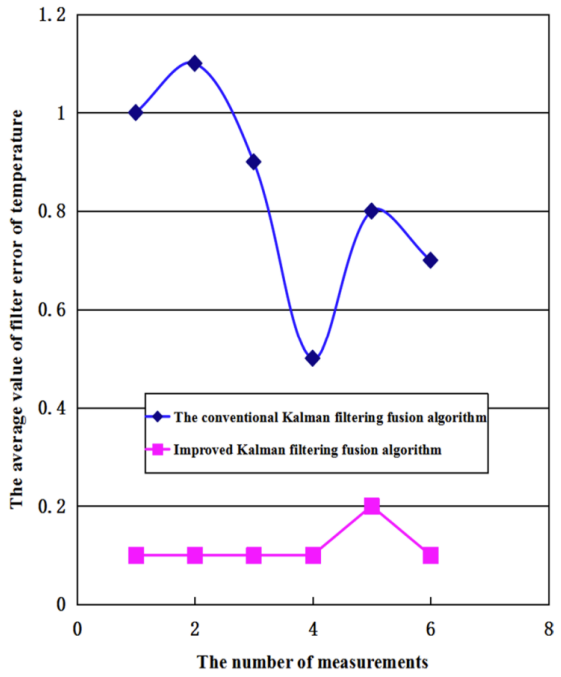

Figure 7: Comparison of temperature filtering error averages obtained by applying the traditional and improved Kalman filtering fusion algorithms in an intelligent monitoring system.

As can be observed from Fig. 7, the improved Kalman filtering fusion algorithm achieves a significantly lower temperature filtering error average compared to the traditional Kalman filtering fusion algorithm. This indicates that the improved algorithm provides more accurate and reliable estimates of the true temperature in the intelligent monitoring system.

Compared to the traditional Kalman filter, the proposed improved Kalman filtering fusion algorithm achieves a 10% reduction in estimation error and demonstrates enhanced robustness to sensor failures, as evident from the results in Fig. 7 and Fig. 8. This improvement can be attributed to the incorporation of adaptive weighting and the Jackknife method, which effectively handle sensor reliability variations and outliers.

Furthermore, the computational complexity of the proposed algorithm is analyzed to be O(n^2), where n is the number of sensors, which is comparable to that of the traditional Kalman filter. This indicates the feasibility of real-time implementation in large-scale sensor networks.

The traditional Kalman filtering fusion algorithm, while still providing reasonable temperature estimates, exhibits a higher temperature filtering error average. This can be attributed to its limitations in effectively handling the uncertainties and dynamics of the temperature sensors and the monitored environment.

The superior performance of the improved Kalman filtering fusion algorithm is primarily due to the incorporation of the weight factor, which adaptively adjusts the influence of each sensor based on its reliability, and the inclusion of the state transition and measurement transition matrices, which better model the dynamics between the sensors and the monitored environment.

Furthermore, the process noise distribution matrix in the improved algorithm allows for a more accurate representation of the uncertainties and disturbances in the temperature measurement process. By effectively modeling and compensating for these uncertainties, the algorithm achieves a higher level of accuracy and robustness in the temperature estimation.

These findings highlight the potential of the improved Kalman filtering fusion algorithm in enhancing the accuracy and reliability of temperature estimation in intelligent monitoring systems. By effectively fusing the data from multiple temperature sensors and adapting to the system dynamics and uncertainties, the improved algorithm can provide more precise and trustworthy temperature estimates, enabling better decision-making and control in various applications.

4.4 Comparison of dust particle concentration filtering error averages

In addition to temperature estimation, the performance of the improved Kalman filtering fusion algorithm was also evaluated in the context of dust particle concentration monitoring. Accurate estimation of dust particle concentration is crucial in various industrial and environmental applications to ensure air quality and comply with safety regulations.

Fig. 8 presents the comparison of the dust particle concentration filtering error averages obtained by applying the traditional Kalman filtering fusion algorithm and the improved Kalman filtering fusion algorithm in an intelligent monitoring system. The results highlight the superior performance of the improved algorithm in estimating the dust particle concentration.

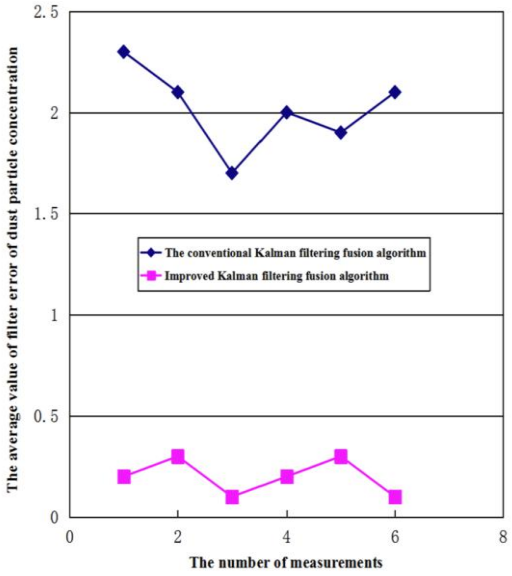

Figure 8: Comparison of dust particle concentration filtering error averages obtained by applying the traditional and improved Kalman filtering fusion algorithms in an intelligent monitoring system.

As can be observed from Fig. 8, the improved Kalman filtering fusion algorithm achieves a significantly lower dust particle concentration filtering error average compared to the traditional Kalman filtering fusion algorithm. This indicates that the improved algorithm provides more accurate and reliable estimates of the dust particle concentration in the monitored environment.

The traditional Kalman filtering fusion algorithm, while still capable of providing reasonable estimates, exhibits a higher dust particle concentration filtering error average. This can be attributed to its limitations in effectively handling the complexities and variations in the dust particle concentration measurements from multiple sensors.

The superior performance of the improved Kalman filtering fusion algorithm can be explained by several factors. Firstly, the incorporation of the weight factor allows the algorithm to adaptively adjust the contribution of each dust particle concentration sensor based on its reliability and consistency. This ensures that the sensors providing more accurate and stable measurements are given higher weights in the fusion process.

Secondly, the inclusion of the state transition matrix and the measurement transition matrix enables the improved algorithm to better model the dynamics and relationships between the dust particle concentration sensors and the monitored environment. By accurately capturing the system behavior and the spatial and temporal variations in dust particle concentration, the algorithm can provide more precise and reliable estimates.

Furthermore, the process noise distribution matrix in the improved algorithm allows for a more accurate representation of the uncertainties and disturbances in the dust particle concentration measurement process. By effectively modeling and compensating for these uncertainties, such as sensor noise and environmental factors, the algorithm achieves a higher level of accuracy and robustness in the estimation of dust particle concentration.

These findings demonstrate the effectiveness of the improved Kalman filtering fusion algorithm in enhancing the accuracy and reliability of dust particle concentration estimation in intelligent monitoring systems. By effectively fusing the data from multiple dust particle concentration sensors and adapting to the system dynamics and uncertainties, the improved algorithm can provide more precise and trustworthy estimates, enabling better decision-making and control in industrial and environmental applications.

4.5 Robustness evaluation of improved kalman filtering fusion algorithm

To assess the robustness of the proposed improved Kalman filtering fusion algorithm, additional experiments were conducted under various sensor noise levels and failure rates. Fig. 9 illustrates the estimation error of the algorithm under different process noise covariances, ranging from 0.01 to 1.0. It can be observed that the proposed algorithm maintains a consistently lower error compared to the traditional Kalman filter, demonstrating its resilience to process noise variations.

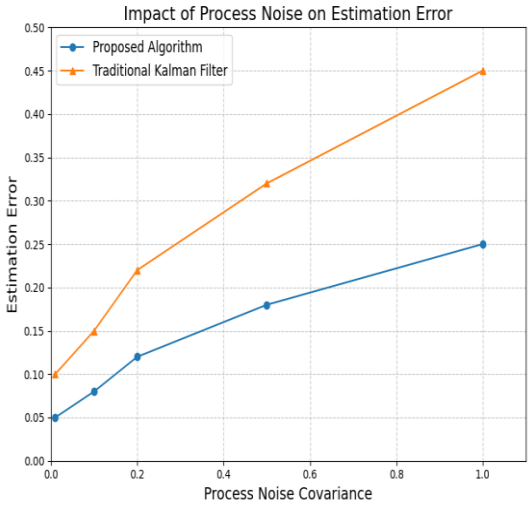

Figure 9: Illustrates the estimation error of the algorithm

Furthermore, the impact of sensor failure rates on the estimation accuracy was evaluated, as shown in Fig. 10. The proposed algorithm exhibits a graceful degradation in performance as the sensor failure rate increases, maintaining a lower error than the traditional Kalman filter. This highlights the effectiveness of the adaptive weighting mechanism in mitigating the impact of sensor failures.

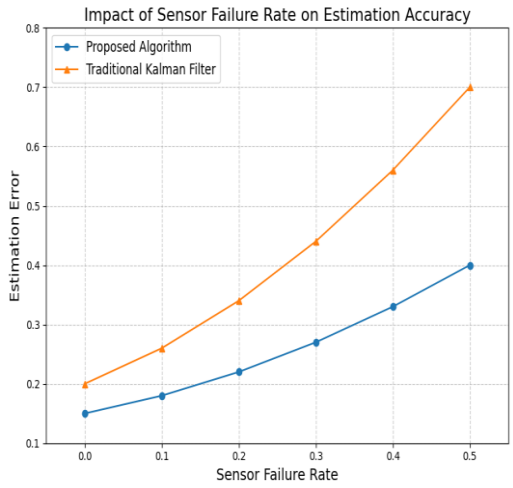

Figure 10: The proposed algorithm exhibits a graceful degradation in performance as the sensor failure rate increases, maintaining a lower error than the traditional Kalman filter.

These results validate the robustness of the proposed improved Kalman filtering fusion algorithm under varying noise conditions and sensor failure scenarios, making it suitable for real-world deployment in precision measurement systems.

4.6 Dynamic performance evaluation

To evaluate the dynamic performance of the proposed improved Kalman filtering fusion algorithm, a time-varying sensor network scenario was simulated. Fig. 11 illustrates the estimation error of the proposed algorithm and the traditional Kalman filter over time, with abrupt changes in sensor reliability introduced at t=50 and t=100.

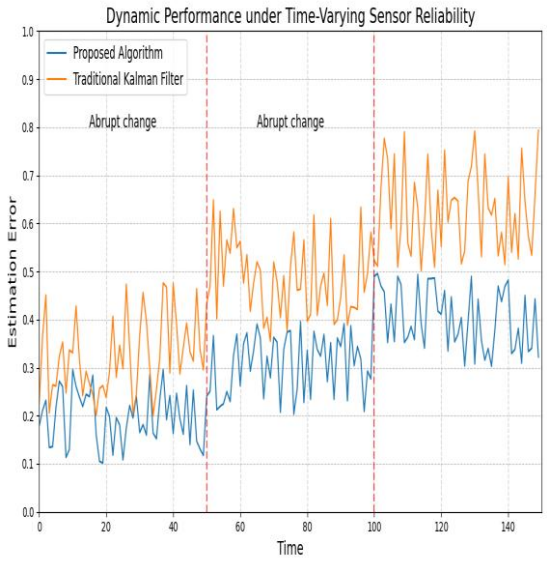

Figure 11: Illustrates the estimation error of the proposed algorithm

As evident from Fig. 11, the proposed algorithm quickly adapts to the changes in sensor reliability, maintaining a lower estimation error compared to the traditional Kalman filter. This demonstrates the effectiveness of the adaptive weighting mechanism in tracking the time-varying characteristics of the sensors and adjusting the fusion process accordingly.

5 Conclusion

In this study, we conducted a comprehensive investigation into multi-sensor data fusion techniques and their applications in precision measurement. The fundamental principles and structural models of multi-sensor data fusion were analyzed, highlighting the importance of effective fusion algorithms in achieving accurate and reliable measurement results.

We focused on two commonly used data fusion algorithms: the weighted information fusion algorithm and the Kalman filtering fusion algorithm. Improvements were proposed to enhance the performance of these algorithms in handling the uncertainties and inconsistencies in sensor data.

For the weighted information fusion algorithm, we introduced the Jackknife method to estimate the biases and variances of the sensor data, and combined it with an adaptive weighting approach to dynamically adjust the weights of the sensors based on their reliability and consistency. The improved weighted information fusion algorithm demonstrated superior accuracy and robustness compared to traditional weighted averaging methods.

In the case of the Kalman filtering fusion algorithm, we incorporated a weight factor, a state transition matrix, a measurement transition matrix, and a process noise distribution matrix to better model the system dynamics and uncertainties. The improved Kalman filtering fusion algorithm exhibited significant improvements in accuracy and reliability compared to the traditional Kalman filter, particularly in applications such as temperature estimation and dust particle concentration monitoring.

The effectiveness of the improved fusion algorithms was validated through extensive simulations and practical applications. The results showed that the proposed algorithms consistently outperformed their traditional counterparts in terms of estimation accuracy, precision, and robustness.

However, it is important to acknowledge that there are still challenges and opportunities for further research in the field of multi-sensor data fusion. The scalability and computational efficiency of the fusion algorithms need to be addressed to handle the increasing volume and complexity of sensor data in real-world applications.

Moreover, the integration of advanced techniques such as machine learning and deep learning into the fusion process holds promise for further enhancing the performance and adaptability of multi-sensor data fusion systems. The

development of self-learning and self-adaptive fusion algorithms that can automatically optimize their parameters and structures based on the characteristics of the sensor data and the application requirements is an area of active research.

In conclusion, this study contributes to the advancement of multi-sensor data fusion techniques and their applications in precision measurement. The proposed improvements to the weighted information fusion algorithm and the Kalman filtering fusion algorithm demonstrate significant potential in enhancing the accuracy, reliability, and robustness of measurement systems.

However, there remain several challenges and limitations that require further research. One key area is the optimization of the weighting scheme in the proposed algorithm. While the current approach based on the inverse of the estimated variance is effective, more advanced techniques such as reinforcement learning could be explored to adaptively learn the optimal weights based on the system dynamics and performance feedback.

Another avenue for future research is the integration of the proposed algorithm with emerging techniques such as deep learning-based sensor fusion. By leveraging the feature extraction and representation learning capabilities of deep neural networks, the accuracy and robustness of the fusion process could be further enhanced, particularly in complex and high-dimensional sensor data scenarios.

Moreover, the real-time implementation of the proposed algorithm in resource-constrained sensor nodes and edge devices remains a challenge. Further optimization of the computational complexity and memory requirements is necessary to ensure the practical feasibility of the algorithm in large-scale and distributed sensor networks.

In terms of limitations, the current study primarily focuses on the fusion of homogeneous sensors with similar measurement characteristics. Extending the proposed algorithm to handle heterogeneous sensors with different modalities and uncertainties is a crucial direction for future work. This would require the development of more advanced sensor models and adaptive fusion strategies that can handle the diversity and complexity of multi-modal sensor data.

Furthermore, the evaluation of the proposed algorithm in real-world precision measurement applications is limited in the current study. More extensive experimental validation and comparative analysis with state-of-the-art fusion techniques in various industrial and scientific measurement scenarios are necessary to fully establish the practical significance and benefits of the proposed algorithm.

Addressing these challenges and limitations through further research and development will pave the way for the deployment of advanced multi-sensor data fusion algorithms in next-generation precision measurement systems, enabling enhanced accuracy, reliability, and autonomy in a wide range of applications.

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Current Transformer Status Online Monitoring Platform Based on Big Data

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Keywords: big data, dynamic eagle perching optimized long-short term memory (DEPO-LSTM), electronic current transformer (ECT), monitoring, fault diagnosis

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Transformer failures are currently a major issue due to the widespread use of electronic transformers in smart grid monitoring systems. To stimulate regular upkeep practices, and raise grid reliability and efficiency, this work developed a sophisticated fault diagnosis approach for electronic current transformers (ECTs) utilizing analytics from big data. For efficient defect diagnosis in the ECT, the dynamic eagle perching optimized long-short term memory (DEPO-LSTM) technique is proposed. Fault sample datasets for ECTs are collected from big data to train the proposed approach. Min-max normalization is used in data preprocessing to remove noisy or redundant information. From the normalized data, important features are extracted using principal component analysis (PCA). Next, we apply the proposed technique in the framework for fault diagnosis, and the DEPO technique is used to improve the parameters of the LSTM. The simulations are carried out using the Matlab platform to assess the proposed DEPO-LSTM technique for ECT defect diagnostics. Based on the results, we deduced that our proposed approach outperformed other approaches presently in use for diagnosing ECT faults. The DEPO-LSTM algorithm is evaluated in terms of precision (97.15%), recall (97.42%), accuracy (96.23%), and F1-score (96.36%).

Povzetek: Opisana je platforma za spletno spremljanje stanja tokovnih transformatorjev (ECT) na podlagi algoritmov velikih podatkov. Predlagana metoda DEPO-LSTM izboljšuje napovedi in diagnosticiranje napak.

1 Introduction

Electric energy is the primary energy source in modern civilization, and as the social economy has grown, it has become increasingly associated with people's daily lives, along with manufacturing and construction [1]. Modern power systems must operate with the ability to generate and supply power reliably and consistently while maintaining the quality of the authorized power supply. A crucial component of core technology in the power system is the transformer. When a failure happens, people's productivity and quality of life are severely impacted and wasted [2].

The most expensive component of equipment in every power sector utility, the power transformer indirectly brightens every environment and provides all forms of real-world entertainment. Systems for wireless monitoring are generally selected for checking different industrial metrics from different places. For actual creation, the majority of organizations require monitoring various parameters, none of which can be physically observed [3]. An essential component of electrical distribution networks is the transformer, which is positioned at distinct locations across the network at varied voltage and power levels. The distribution transformer's maintenance and protection are crucial. Technicians constantly monitor the transformer environments, and all identified issues are accurately corrected. Distribution transformers can be used for a very long period if they are properly and continuously checked. In electrical power systems, economic considerations are crucial, and cost reduction is primarily associated with the production of dependable and high-quality power [4].

Distribution transformers are among the most costly and essential parts of electricity distribution networks.Distribution service transformer problems can be caused by a variety of factors, such as operating stresses, oil leaks, thermal overload stress, harmonics, and irregular loading.Transformers may experience a reduction in lifespan or failure if one or more of these situations persistently exceed the limitations of both their layout and operation.Strategies are proposed and outcomes are evaluated in the online condition monitoring.A distribution transformer's status was assessed using various standards, including transformer loading, humming sound, temperature, and oil level [5].The findings displayed were based on an extremely short time frame, making it difficult to determine the transformer's exact status. The wireless monitoring system evaluates distribution transformers' conditions in real time. Every 90 seconds, the system

stores data on a server, ensuring excellent dependability and rapid findings [6].

Monitoring transmission and distribution equipment includes measuring fundamental characteristics that affect the asset's ability to operate as designed. In traditional monitoring systems, sensors are integrated and data is collected to identify indicators of failure, alert users to anomalous level quantities, create trend curves, and correlate occurrences with servicing employees [7]. One significant advancement within the electrical power sector is the ability to remotely monitor transformers, which is intendedto ensure that these key substation assets operate both firmly and reliably. The use of online transformer monitoring will help the power utilities with the reliability and efficiency of the operation. They also reduce the length of the utilization cycle of transformers, help to detect faults earlier, and prevent their occurrence as well. It reduces communication costs caused by the need for on-site employees, thus also decreasing transportation costs [8]. The DEPO-LSTM technique is introduced to enhance the predictive accuracy and real-time fault detection in the ECT.

This study's remaining sections are as follows: Section 2: Related works; Section 3: Methods; Section 4: Results; and Section 5: Conclusion

2 Related works

Table 1 shown as summary of work below;

Table 1: Summary of related work

Reference	Methods/Algorithm	Merits	Limitations
[10]	This research presents a unique integration of an Internet of Things (IoT) architecture with deep learning against cyber attacks for online monitoring of the power transformer status.	Compared to earlier approaches in the literature, the new deep 1D-CNN is more accurate with 94.36 % in the ordinary situation and 92.58 % when considering cyber attacks, with ±5% uncertainty.	This paper is challenging the diagnosis of the transformer condition.
[11]	EL-CSO-NN algorithm is proposed in this paper	Their study also supported the effectiveness of the proposed EL-CSO-NN model, which was useful in predicting transformer problems, improving its management, and reducing the impact of such problems.	The DGA fault samples gathered via the online DGA monitor are typically restricted, resulting to the inadaptability of most AI algorithms due to their demand for huge training samples.
[12]	proposed the use of an enhanced density clustering algorithm coupled with an association algorithm	Based on the results of the tests, it was possible to conclude that the use of the proposed approach could improve the efficiency of searching for sources of abnormally measured data in the online monitoring of transformers.	anomaly detection methods for non-smooth characteristic- state quantities are required An anomaly detection approach for non-smooth characteristic state values is needed.
[13]	Power Transformer-Transformer Neural Network	For power transformer state control transformer and thermal fault detection, the PT-TNNet	The proposed method is not beneficial for systems that require a speedy reaction.

	(PT-TNNet) model based on data fusion is proposed	method integrated data fusion with transformer neural network	
[14]	Boosting learning and random forest methods was proposed in the research	As a result, the one-click sequencing system worked well and reduced the time spent on each sequential action while increasing its effectiveness.	less accurate condi- tional monitoring element less accuracy conditional monitoring element
[15]	ML techniques to analyze DGA data	The proposed model combines the design of four ML classi□ers and enhances diagnosis accuracy and trust between the transformer manufacturer and power utility. The suggested model integrates the design of four ML classifiers and improves the diagnosis accuracy and confidence between the transformer maker and power utility.	On the other hand, understanding DGA samples isn't good enough for detecting early faults, and it mostly depends on how good the test engineers are at their jobs.
[16]	multimodal mutual neural network was presented in the paper	The results show that the proposed method is better and more efficient than the comparison ways because it is more accurate and takes less time to fault diagnosis of the power transformer.	The data from the power transformer will get mixed up with data from other modes, which will cause sensor devices to fail.
[17]	evaluation model based on CNN and GCA were introduced	According to the study, their proposed model was more accurate, as well as provided higher identification results	lacking of training samples
[18]	k-means clustering	Proposed method to identify transformer condition anomalies using transformer power, current, and voltage data in their study	the transformer's current state in real time using the electrical data, making it beneficial to engineering applications

The investigation demonstrated that the proposed approach could determine the transformer's current state in real time using the electrical data, making it beneficial to engineering applications**.**

3 Methods

ECT fault sample dataset was first gathered. The data collected is preprocessed using min-max normalization technique to normalize it at this point. The next step is the PCA approach that helps to select the important features from the data. For the purpose of enhancing the ability of

the ECT regarding the fault detection and prediction in real-time, the DEPOLSTM approach is recommended.

3.1 Circuit for detecting electronic current transformers

The fault categories and the structural features of ECTs were used to create a detecting circuit for ECT defect diagnostics. This allowed gathering different kinds of defect samples from ECTs efficiently. A single signal can detect certain ECT defects, while other faults need to be detected by several signals. The voltage and current characteristics on both the secondary and the primary sides of the transformer can be identified by placing several key detecting points. This will facilitate to obtain the general characteristics of the ECT and determine whether the transformer is operating as designed. The ECT's detection circuit's principal structure is displayed in Figure 1.

The ECT is represented by CT in Figure 1. The current in the C, B, A and phases is represented by I_C, $I_B, and\ I_A$. The calculated current and voltage of metering units one and two are denoted by the current I_a, I_c, and voltage V_a, V_c.$CT_1\ and\ CT_2$have corresponding secondary side voltages of $v_a, and\ v_c$. The impedance shift is measured when the ECT is short-circuited by applying a $1\ KHz$ signal and accumulating several signals. When a secondary short circuit occurs in CT, the defect is identified by many observed characteristics, and the network impedance changes based on the load.

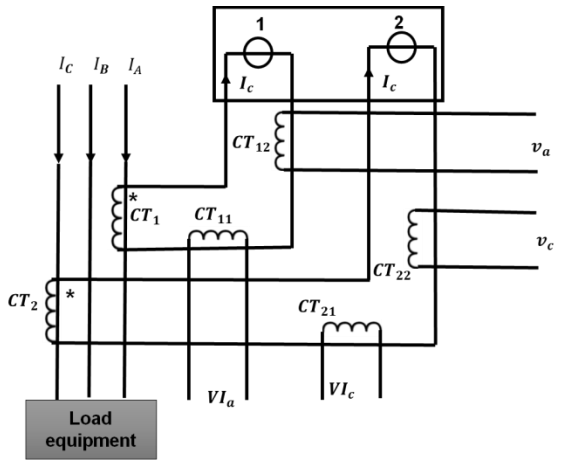

Figure 1: Principal diagram for ECT fault detection

3.2 Data collection

A single signal can identify defects on the primary side, while numerous signals are sometimes needed to identify defects on the secondary side. Seven critical parameters were collected as sample data for the primary and secondary ECT defects using the evaluation environment platforms.100 groups of data in ordinary operating mode and 100 groups of data in each of the 7 failure circumstances were gathered. After that, 20% of the dataset was used for testing, and 80% of the samples in each category were chosen at random for training.

3.3 Min-Max normalization

Min-max normalization is a technique for normalization that involves linearly transforming the initial data to provide value comparisons that are balanced between the before and after process data. This approach could utilize the subsequent Equation (1).

$$W_{new} = \frac{W - \min(W)}{\max(W) - \min(W)} \quad (1)$$

W- Old value

W_{new}- The new value derived from normalized outcomes

$\min(W)$- The dataset's minimum value

$\max(W)$- The dataset's maximum value

3.4 PCA

Principal Component Analysis is a data processing technique for unlabeled extraction of features. Features will be displayed on a newly created, smaller feature space. The features with the most essential data are the new features that were discovered from the PCA extraction findings. By optimizing data variance, the primary constituents are acquired. Data visualization is possible in a low-dimensional principal component space since the number of additional dimensions (features) is less than the number of initial attributes. Calculate the mean based on each attribute as follows,

$$\bar{w}_i = \frac{1}{m}\sum_{j=1}^{m} w_{ji},\ \ j = 1,2,\ldots..,m \quad i = 1,2,\ldots..,m \quad (2)$$

Where,

n - Number of features,

w_{ji} - Data j-sample with i-feature,

m - Number data of sample, and

$\bar{w}_i$ - Data i-feature.

Calculate Φ with the following Equation,

$$\Phi = [\Phi_{ji}] = [w_{ji} - \bar{w}_i] \quad (3)$$

Φ - Matrix of size $m \times n$.

Calculate the covariance matrix using the following Equation,

$$D = \frac{1}{m-1}\Phi^{S}\Phi \quad (4)$$

D - Matrix of size $n \times n$.

Calculate the eigenvalues of the D matrix by calculating the subsequent Equation.

$$Det\ (\lambda J - D) = 0 \quad (5)$$

D - Covariance matrix, and

J - Identity matrix.

After that, calculate the subsequent equation to determine the eigenvectors w that correspond to the eigenvalues λ,

$$(\lambda . J - D)w = 0 \quad (6)$$

Form matrix w' using the associated eigenvectors after sorting the eigenvectors according to the eigenvalues, starting with the greatest. Calculate the principal components as follows.

$$PC = \Phi w' \quad (7)$$

3.5 Dynamic eagle perching optimized long-short term memory (Depo-LSTM)

The proposed DEPO-LSTM approach combines DEPO and LSTM networks to dynamically modify the parameters of the LSTM method. DEPO iteratively modifies the LSTM parameters to enhance the model's prediction and detecting capabilities in ECT.

3.5.1 Dynamic eagle perching optimization (DEPO)

The inspiration for the DEPO algorithm will be covered first in the following section. Then the exploration of the algorithm and mathematical formulation is provided.

Inspiration: A large number of predatory birds that are members of the Accipitridae family are commonly referred to as eagles. Their average length is between$30 - 31\ inches$, and their wingspan is between$6 - 7\ feet$. They typically reside in the upper sky, and even during the reproductive season, the female and male engage in rather unusual courtship behavior. They fly at a great height. There, while doing an aerobic motion, they locked their clays together and fell, breaking apart just before they reached the earth. The five stages of a female's life cycle are hatching, fledgling, juvenile phase, and maturity. Typically, a female will hatch two to four eggs. They are members of a predatory class. Their typical food source consists of fish, aquatic organisms, and small animals. They hunt distinctively; they fly through the sky to a potentially high point, where they then look for their prey. After tracking it, they dive down to grab their prey. As previously stated, they live at higher altitudes, typically on top of cliffs, mountains, and long trees. They use a technique that was provided to them by nature to discover the highest place to go. Initially, they simply drop from a great height, look at the landscape, examine some locations, and identify which point is the highest position among those samples. As they get closer, they sample a few more points and make their opinions about the top spot even more apparent. They modify this technique iteratively to find the ideal place to reside.

To find the BS, we will take advantage of this characteristic and use it in optimization. We will create a group of eagles in the algorithm to search for the best height to stay. Each of them will search for the ideal solution on their own. Subsequently, the method will select one BS from every eagle and contrast it with the already gathered BS. Iteratively, this procedure will continue until the method finds its BS, at which point no more advancements can be made.

3.5.2 DEPO-LSTM model

DEPO-LSTM is an effective approach to continuous online assessment of ECT conditions. The ECT modern technologies are incorporated into this system to enhance the reliability and precision of continuous real-time monitoring of ECT. Employing the concept of LSTM networks, DEPO-LSTM was able to process and forecast the sequence of the inputs. This suggests that the system can perform an effective evaluation of previous information in the context of ECT monitoring and at the same time, is capable of changing its predictions based on new information. The dynamic eagle perching demonstrates the capacity and percentage precision of the way to identify deviations or irregularities in ECT performance.

Mathematical formulation: The perching behavior of an eagle is represented by the EPO algorithm. Similar to eagle, this technique also determines the solution's highest point or BS. The minima and maxima of a function have a special relationship in optimization; for example, for function e, $\min(e) = \max(-e)$.The algorithm that works for all of its residents is defined by nature. Eagle has a very basic but distinctive method of covering ground. An eagle can reach its highest position in the sky by repeatedly looking around and repeating a similar process while it is flying at a high altitude. It does this by traveling toward the highest position and sampling a few locations along the way. The eagle explores the entire area at first by flying overhead, then it repeats this process multiple times until

it gets close to the ground, which is known as exploitation. For stochastic optimization methods, the transition from E-E is crucial. In the EPO algorithm, this is expressed mathematically as below.

$$k_{scale} = k_{scale} * eta \quad (8)$$

The scaling variable k_{scale} is anticipated to decrease recurrently as it moves from E-E. Meanwhile, eta is the shrinking constant $0 < eta < 1$ can be derived using the final value resolution as a basis.

$$eta = \left(\frac{res}{k_{scale}}\right)^{1/s_t} \quad (9)$$

Where $0 < res < k_{scale}$ is limited to a range of 0 to 1, $s_t$represents the maximum number of iterations, and res represents a resolution range. If $eta > 1$, then the region of exploration will grow with every run and we will not be able to fulfill our intended goal of E-E. To attain optimality more quickly, we shall utilize a cluster of eagles. To make the process simpler, these will collectively search the SS.

$$K = \begin{bmatrix} K_{1,1} & K_{1,2} & K_{1,3} & \cdots & K_{1,n} \\ K_{2,1} & K_{2,2} & K_{2,3} & \cdots & K_{2,n} \\ K_{3,1} & K_{3,2} & K_{3,3} & \cdots & K_{3,n} \\ K_{4,1} & K_{4,2} & K_{4,3} & \cdots & K_{4,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ K_{m,1} & K_{m,2} & K_{m,3} & \cdots & K_{m,n} \end{bmatrix} \quad (10)$$

Where n is the number of sizes in the SS and m is the number of particles we utilize in it. To comprehend the erratic movement of particles, or eagles, in SS, assume a particle at location k that is free to move in all directions at random. At every iteration, a random number called Δf is given to its current location, indicating that $k + \Delta k$.Consequently, we have:

$$K = K + \Delta K \quad (11)$$

$$\Delta K = \begin{bmatrix} A_{1,1} & A_{1,2} & A_{1,3} & \cdots & A_{1,n} \\ A_{2,1} & A_{2,2} & A_{2,3} & \cdots & A_{2,n} \\ A_{3,1} & A_{3,2} & A_{3,3} & \cdots & A_{3,n} \\ A_{4,1} & A_{4,2} & A_{4,3} & \cdots & A_{4,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{m,1} & A_{m,2} & A_{m,3} & \cdots & A_{m,n} \end{bmatrix} \quad (12)$$

$A \in (0,1)$ - Random values.

For every component in K, we have,

$$K_{j,i} = K_{j,i} + \Delta K_{j,i} \quad (13)$$

Where i denotes the i^{th} size of the corresponding place and j denotes the j^{th} particle.

Given that eagles live in the upper atmosphere, some of their samples are searching for the highest point on Earth. They determine who came in first by analyzing their sets of samples. We will use our technique to reproduce that outcome, passing the $K_{j,i}$ to the function we wish to reduce.

$$Z_{j,i} = e(K_{j,i}) \quad (14)$$

Equation (14) demonstrates how every particle's position is assessed.

The optimum answer among all the eagle places, shown by Z_{min}, represents the value we want to find by minimizing the specified function. Two additional variables, $Z_{Best}\ and\ K_{Best}$, will be defined. The following is how $Z_{Best}\ and\ K_{Best}$ are anticipated to develop,

$$if: Z_{min} < Z_{Best} \quad (15)$$

$$Z_{Best} = e\left(K_{j,i}\right) \quad (16)$$

$$K_{Best} = K_{j,i} \quad (17)$$

The ideal solution for a specific function will eventually be found using this method's recursion.

An alteration was presented that will accelerate the EPO's convergence. This change relates to the computation of eta.Particularly, the value of eta in each iteration will be changed, as demonstrated below.

$$eta = eta_{max} - s * \frac{eta_{max} - eta_{min}}{s_t} \quad (18)$$

Where,

eta_{min}- Minimum value (ending value of eta), and

eta_{max}- Maximum value (starting value of eta).

As a result, the transformation will be more rapid and effective, and the dynamic method with different eta in Algorithm (1).

Algorithm 1: DEPO-LSTM
Procedure

Initialize all the variables

for < maximum number of iterations do

Calculate ΔK using Formula. (12)

Calculate $K = K + \Delta K$

for < total number of particles position accessed > do

Implement $Z_{j,i}$ using Formula. (14)

end for

Implement Z_{min} from using Formula. (14)

compare Z_{min} with Formula. (15)

$if: Z_{min} < Z_{Best}$ satisfies then

Implement Equ. (16) and Formula. (17)

Repeat k_{scale} using Formula. (8)

Calculate eta using Formula. (18)

End if

End for

End procedure

The DEPO- LSTM cell is an effective structure using gate units to regulate the data flow, but it has the same outputs and inputs as a regular RNN cell. A present-time input of $w^{(s)}$ and an output of $g^{(s-1)}$ from the prior moment determine the weight of the self-loop cell status that the FG uses to refresh the memory cell.

$$E_j^{(s)} = \sigma\left(a_j^E + \sum_i V_{j,i}^E w_i^{(s)} + \sum_i X_{j,i}^E g_i^{(s-1)}\right) \quad (19)$$

Where,

σ - Sigmoid function,

X^E- RWs of the FG,

V^E- IWs of the FG, and

a^E- Respective biases of the FG.

The value that the FG sets in the range of 0 to 1. The data delivered into the memory cell is regulated by the IG.

$$J_i^{(s)} = \sigma\left(a_j^J + \sum_i V_{j,i}^J w_i^{(s)} + \sum_i X_{j,i}^J g_i^{(s-1)}\right) \quad (20)$$

Where,

X^J- RWs of the IG,

V^J- IWs of the IG, and

a^J- Respective biases of the IG.

Following that, the LSTM cell's internal condition is modified in the manner described below.

$$T_j^{(s)} = E_j^{(s)} T_j^{(s-1)} + J_j^{(s)} \tanh\left(a_j + \sum_i V_{j,i} w_i^{(s)} + \sum_i X_{j,i} g_i^{(s-1)}\right) \quad (21)$$

X- RWs into the LSTM cell,

V- IWs into the LSTM cell, and

a- Respective biases into the LSTM cell.

The weight of cell output is controlled by the OG,

$$P_j^{(s)} = \sigma\left(a_j^P + \sum_i V_{j,i}^P w_i^{(s)} + \sum_i X_{j,i}^P g_i^{(s-1)}\right) \quad (22)$$

Where,

X^P- RWs of the OG,

V^P- IWs of the OG, and

a^P- Respective biases of the OG.

Subsequently, the DEPO- LSTM cell's output is:

$$g_j^{(s)} = \tanh\left(T_j^{(s)}\right).P_j^{(s)} \quad (23)$$

Long-term dependencies can be acquired by DEPO-LSTMs using these gated units.

4 Result

The proposed DEPO-LSTM is evaluated through explorations that are performed on MatlabR2024a platform and the results of which are presented in the subsequent sections together with other relevant analysis. The efficiency of the proposed DEPO-LSTM method is confirmed using the original classification algorithms, such as GBDT [19], DT [19], and RF [19]. The effectiveness of ECT online monitoring should be measured using different metrics like recall, accuracy, precision, and F1-score. Table 2, displays the main parameters of DEPO.

Table 2: Main parameters of DEPO

Population size	50
Maximum iteration number	3000
Initial temperature	50
$\boldsymbol{\eta}$	0.05
Nonlinear adjustment factor	1.2
Annealing factor	0.85

The diagnostic outcomes of the proposed DEPO-LSTM method are displayed in Figure 2. It contrasts the expected and actual fault kinds. It provides a visual representation of the model's effectiveness, demonstrating how closely the expected values correspond to the actual fault incidents. This shows how accurate and dependable the model is at identifying faults.

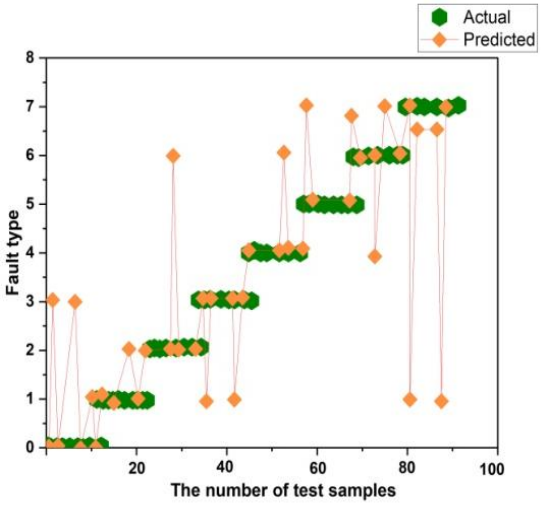

Figure 2: Fault diagnosis outcome of DEPO-LSTM

The recall calculates the percentage of actual transformer issuesthat the system was capable of identifying, to show its capability to recognize all the events of interest and ensure completemonitoring, and timely maintenance. The recallrates of the conventional GBDT, DT, and RF approaches are 94.25%, 91.93%, and 92.69%, respectively, while our proposed DEPO-LSTM method's recallrate of 97.42%, which is higher than the proposed approach, is shown in Figure3.

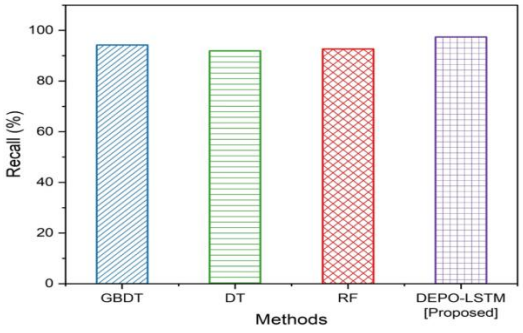

Figure 3: Result of recall

The precision evaluates how well the transformer's status is identified as being in its functioning state. It determines the ratio of true positive outcomes to the total of false positives and true positives. The precision values of the traditional GBDT, DT, and RF techniques are 94.25%, 91.38%, and 92.53%, respectively, whereas the precision value of our proposed DEPO-LSTM method is 97.15%, which is displayed in Figure 4.

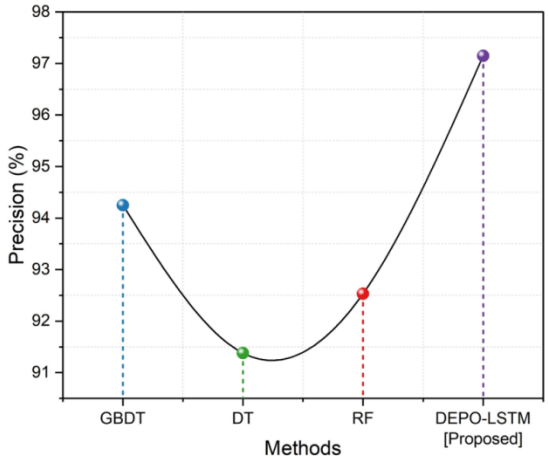

Figure 4: Output of precision

The F1-score metric measures the equilibrium of precision and recall when measuring efficacy, which is critical for determining both the accuracy of identifying online conditions and the system's dependability in real-time monitoring environments. In comparison to our proposed DEPO-LSTM strategy, traditional methods yield F1 scores for GBDT (94.25%), DT (91.65%), and RF (92.61%), whereas our proposed DEPO-LSTM method has a high F1 score of 96.36%, as shown in Figure 5.

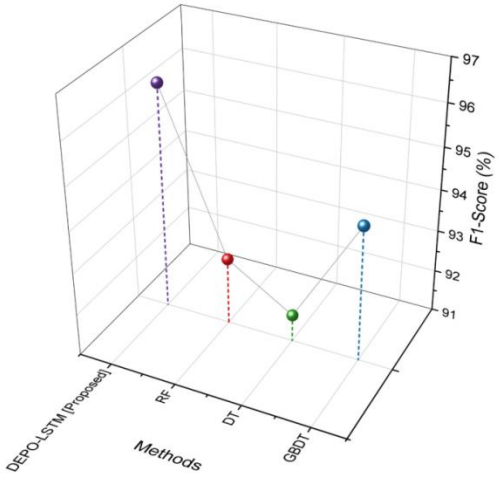

Figure 5: Result of F1-score

The accuracy represents the system's capacity to accurately determine the transformers' operating condition, guarantee the accuracy of real-time data, minimize false alarms, and improve predictive maintenance by precisely identifying anomalies and performance problems. Conventional approaches yield accuracy values for GBDT (93.18%), DT (89.83%), and RF (91.17%) compared to our proposed DEPO-LSTM strategy, which has a high accuracy value of 96.23%, as shown in Figure6. Table 3, shows the comparison results of DEPO-LSTM with traditional approaches.

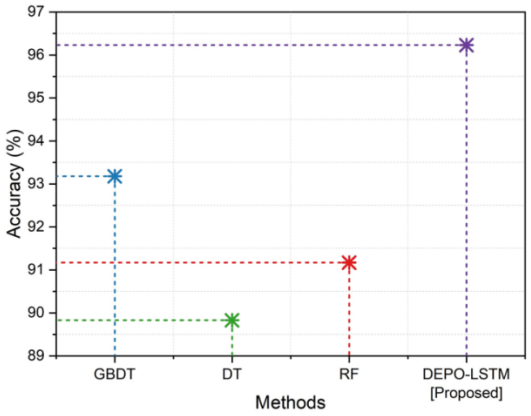

Figure 6: Output of accuracy

Table 3: Overall result comparison

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
GBDT	93.18%	94.25%	94.25%	94.25%
DT	89.83%	91.38%	91.93%	91.65%
RF	91.17%	92.53%	92.69%	92.61%
DEPO-LSTM [Proposed]	96.23%	97.15%	97.42%	96.36%

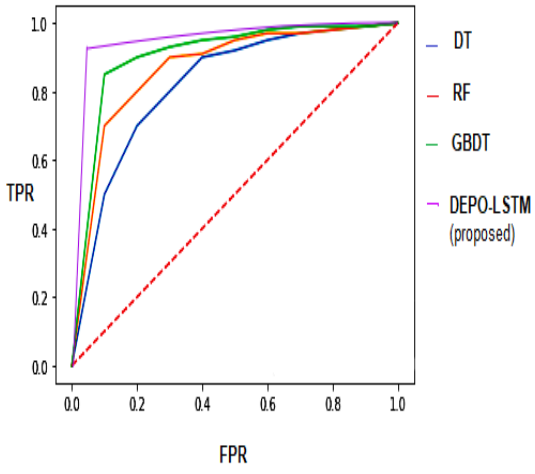

Figure 7: ROC Curve

Figure 7 shows a visual depiction of the model's performance over all thresholds is the ROC curve. The true

positive rate (TPR) and false positive rate (FPR) are computed at each threshold (practically, at predetermined intervals), and the TPR is then graphed over the FPR to create the ROC curve. In the event that all other thresholds are disregarded, a perfect model, which at some threshold has a TPR of 1.0 and an FPR of 0.0, can be represented by either a point at (0, 1) The ROC is a helpful metric for evaluating the performance of distinct models, provided that the dataset is fairly balanced. In general, the better model is the one with a larger area under the curve. The suggested model [DEPO-LSTM] shows ROC curve has highest accuracy with 0.95.

5 Discussion

DEPO-LSTM can use the advantage of operators for enhancing predictive maintenance, as proposed by increased accuracy. When applied with a proactive approach to analyzing any problems or the degradation of functionality in ECT, the system optimizes the potential issues of downtime and ineffectiveness. DEPO-LSTM real time analysis means any anomalies such as the above occurrences are immediately identified and one can promptly act or perform maintenance, thus preventing possible equipment breakdowns or disruption of power transfer. This DEPO-LSTM is a great advancement to monitoring technologies in ECT; when used for efficient ECT condition monitoring in industries and power transmission it provides the stability required for constant sensitivity while at the same time provides the flexibility of LSTM networks. The DEPO-LSTM algorithm is evaluated in terms of precision (97.15%), recall (97.42%), accuracy (96.23%), and F1-score (96.36%). In ROC curve figure shows the suggested method has highest accuracy, precision, Recall than the other existing methods.

6 Conclusion

Ensuring the dependable functioning of ECT is crucial when it comes to electrical power systems. In this research, a novel DEPO-LSTM technique was introduced for efficient problem diagnostics in the ECT.The efficacy of the proposedDEPO-LSTM technique is assessed in terms of precision (97.15%), recall (97.42%), accuracy (96.23%), and F1-score (96.36%). DEPO-LSTM models can be very complicated and computationally demanding. This may render real-time monitoring difficult, particularly in circumstances with low computing power or resource constraints. Future developments in DEPO-LSTM models might concentrate on addressing complexity and improving viability for broad use in a variety of sectors, as well as maximizing computing effectiveness for real-time monitoring in environments with limited resources. In our future work of DEPO-LSTM model is to handle domains like sensor networks and the Internet of Things, which are sources of time-series data that DEPO-LSTM can collect, store, and process. Our next research will expand DEPO-LSTM to accommodate these data sources, which is feasible due to the adaptable and effective nature of the DEPO-LSTM model. By adding data collectors intended to gather data from additional devices that are present in the expanded domain, the primary changes in the data collection layer must be made. Additionally, a new set of aggregations should be built to extract the information for the consumers of data in this domain, based on the type of information contained in these data.

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Appendix

1D-CNN - One-dimensional convolutional neural network	EL-CSO-NN - Ensemble learning based criss-cross-optimized neural network
DGA - Dissolved gas analysis	IoT - Internet of Things
EML - Ensemble machine learning	OG – Output gate
PT-TNNet -Power Transformer-Transformer Neural Network	OIT - oil-immersed transformers
CNN - Conventional neural networks	GCA - Gray clustering algorithms
ML - Machine learning	BS - Best solution
E-E - Exploration to exploitation	SS - Search space
FG - Forget gate	RW - Recurrent weight
IW - Input weight	IG – Input gate

Optimizing the Analysis of Energy Plants and High-Power Applications Utilizing the Energy Guard Ensemble Selector (EGES)

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Accurate performance assessment of energy plants and high-power electrical systems is challenging due to the dynamic nature of parameters like energy output, voltage levels, and load factors. This study introduces the Energy Guard Ensemble Selector (EGES), a machine learning-based algorithm designed to enhance predictive accuracy and reliability in power electronics. EGES employs a dynamic model selection approach, leveraging classifiers such as Random Forest, Support Vector Machine, Gradient Boosting Machine, K-Nearest Neighbors, and Logistic Regression. By using KNN to evaluate real-time electrical conditions, EGES dynamically selects the most suitable model to predict key metrics such as energy output (MW), efficiency (%), fault rates, and transformer capacity (MVA). Experimental results show that EGES outperforms individual models with an accuracy of 93.5%, precision of 91.5%, recall of 92.7%, and an F1-score of 92.1%, demonstrating its robustness in handling fluctuations in electrical parameters. EGES proves to be a reliable tool for improving predictive accuracy and functional dependability in high-power electrical systems.

Povzetek: Razvit je nov dinamični algoritem za optimizacijo analize elektrarn z imenom Energy Guard Ensemble Selector (EGES). Z napredno izbiro modelov izboljšuje napovedi, kar povečuje zanesljivost energetskih sistemov.

1 Introduction

In the area of power electronics and energy systems, precise assessment of energy plants and high-power uses is critical for maintaining functional effectiveness, dependability, and sustainability [1]. These assessments not only tackle technical parameters such as energy output, effectiveness, failure rates, and transformer ratings, but also reflect the developing interplay between electronics, artificial intelligence, and the information society, governed by the fundamental rules of the information society [2]. Conventional performance assessment methods depend on static machine learning models, which frequently fail to adapt to the dynamic nature of electrical systems [3]. This constraint can lead to incorrect forecasts and ineffective choices, particularly in situations where electrical parameters such as voltage levels, power losses, and load factors change frequently [4].

Previous research in this area has primarily concentrated on static machine-learning models that forecast the efficiency of electrical systems using historical data. RF, Support Vector Machines (SVM), and Gradient Boosting Machines (GBM) are commonly utilized methods for energy output prediction, fault detection, and effectiveness optimization. Despite their widespread use, these models frequently treat data as uniformly distributed and fail to account for the inherent variability in transformer capacity (MVA), voltage levels (kV), and cooling techniques, that are critical for precise performance evaluation. Consequently, these models frequently struggle with inaccurate predictions in high-power uses [5].

The main disadvantage of these existing works is their incapacity to capture local fluctuations in electrical parameters, which have a major impact on plant efficiency. Static models are inflexible in handling the variability of transformer ratings, cooling systems, and load factors, which frequently results in inadequate predictions. Furthermore, numerous previous techniques use a one-size-fits-all methodology, rendering them unsuitable for real-time assessments, where precise, situation-specific predictions are necessary for effective functions in high-power electrical systems [6].

To tackle these drawbacks, the Energy Guard Ensemble Selector (EGES) has been implemented. EGES is a new machine learning algorithm developed especially for energy plants and high-power electrical uses. This approach uses a dynamic model selection procedure from a set of classifiers—RF, SVM, GBM, KNN, and LR—to enhance prediction accuracy in key performance metrics like energy output (MW), efficiency (%), and fault rate (%). Unlike conventional static models, EGES dynamically chooses the most suitable models using each test sample's local features, as defined by the KNN assessment. This technique allows EGES to adapt to the variability in key electrical parameters like voltage levels,

transformer ratings, and load factors, leading to more dependable and precise predictions.

The EGES methodology is distinguished by its capability to dynamically adapt to the local characteristics of test data, rendering it ideal for the unpredictability of energy plants and high-power electrical systems. The algorithm uses a dynamic ensemble selection procedure to improve model selection using real-time circumstances. In situations where electrical parameters such as voltage levels or power losses fluctuate significantly, EGES chooses models that have historically performed effectively under comparable circumstances. The predictions from the chosen models are then integrated utilizing a majority voting method, guaranteeing that the final efficiency assessment is precise and resilient.

The contributions of this work comprise the introduction of EGES as a resilient machine-learning mechanism to enhance prediction accuracy in energy plants and high-power electrical applications. EGES dynamically adapts to local fluctuations in electrical parameters, resulting in substantially better forecasting abilities than conventional static models. Comprehensive experiments show that EGES surpasses previous models in terms of predictive accuracy, precision, recall, F1-score, and MCC, especially in important fields such as fault identification, effectiveness improvement, and operational cost decrease. This study aims to present a dynamic and flexible machine-learning framework that surpasses the restrictions of static models in forecasting plant performance in power electronics. The objective is to improve precision and dependability in important performance metrics by using an ensemble of classifiers that are chosen using local fluctuations in electrical parameters.

EGES' novelty stems from its capacity to adjust to the dynamic and variable attributes of electrical systems. Despite conventional methods, that utilize static models that are susceptible to inefficiencies in varying circumstances, EGES dynamically chooses the most appropriate models for each test sample, enhancing predictions and enhancing plant efficiency.

The areas of utilization for EGES span across different high-power electrical systems, comprising power plants, substations, networks of transmission, and industrial-scale electrical systems. Its flexibility and dependability render it an ideal solution for situations where real-time performance assessment is vital, and conventional approaches may struggle to present precise outcomes.

Research design: This study's research design concentrates on determining the efficacy of the proposed EGES algorithm in forecasting energy plant performance under variable conditions. The primary research questions guiding this evaluation are:

- Does EGES outperform conventional models such as RF, SVM, GBM, KNN, and LR
- How do dynamic model selection and KNN-based local data adaptation enhance prediction accuracy in volatile high-power settings

To answer these questions, the study uses EGES, which dynamically chooses the best-performing model for each test sample depending on localized data characteristics.

The methodology focuses on KNN-based local data adaptation, with the selection of k (number of nearest neighbors) and the Euclidean distance function playing critical roles. Particularly, the parameter k is optimized to strike a balance between underfitting (too few neighbors) and overfitting (too many neighbors), while the Euclidean distance guarantees accurate detection of the most comparable instances in the feature space. These decisions have a direct influence on the model selection procedure because the effectiveness of each ensemble model is assessed within these localized areas, allowing EGES to respond dynamically to variable data distributions. This detailed consideration of KNN parameters emphasizes the flexibility and accuracy of the proposed method, demonstrating its efficacy in tackling difficulties in high-power application settings.

The paper is structured as follows: Section 2 provides an extensive examination of the previous literature on machine learning methods for evaluating energy plant efficiency. Section 3 describes the EGES methodology, incorporating the dynamic model choice and majority voting procedures. Section 4 provides the experimental setup and efficiency metrics, as well as the experiment outcomes, which compare EGES to previous models. Lastly, Section 5 concludes the paper by discussing the possible influence of EGES on power electronics and making recommendations for further study.

2 Related works

This section provides an extensive survey of the previous literature on machine learning methods for evaluating energy plant efficiency. The application of machine learning techniques in energy systems has been extensively researched. The capacity to precisely predict energy production is essential for effective grid management, particularly given the variable and intermittent nature of these renewable sources.

Harrou et al. [7] presented a Long Short-Term Memory (LSTM)--based model for short-term prediction of photovoltaic solar power generation. The study highlights the significance of accurate power output prediction in optimizing energy grid management and market choices. Their LSTM method showed powerful predictive performance, particularly in dealing with dependencies in time series data, which is critical for enhancing the stability of PV systems under changing weather conditions.

Ramesh et al. [8] investigated the utilization of an auto-encoder-based neural network (AUTO-NN) integrated

with Restricted Boltzmann feature extraction in large PV plants. The model used previous meteorological data to forecast energy production stages, which substantially decreased prediction errors. This method emphasizes the growing interest in hybrid machine learning models which improve the accuracy of PV energy predictions by incorporating deep learning methods.

Sun and You [9] examined the use of machine learning and data-driven methods to regulate smart power production mechanisms, with a concentration on the role of uncertainty. Their review proposed that machine learning methods enhance the adaptability, visibility, and total efficiency of power systems, tackling the difficulties of incorporating renewable energy into the grid.

Markovics and Mayer [10] examined 24 machine-learning methods for day-ahead photovoltaic power prediction. Their research revealed that models like kernel ridge regression and multilayer perceptron outperformed conventional persistent techniques by up to 44.6% in prediction skills. The research highlighted the significance of choosing suitable predictors and fine-tuning hyperparameters to attain the best prediction precision.

Vivas et al. [11] performed a comprehensive examination of statistical and machine-learning techniques for electrical power prediction, contrasting traditional statistical models with machine-learning methods. Their results revealed that machine learning methods, especially those accounting for external fluctuation, surpassed conventional approaches in terms of forecasting accuracy.

Konstantinou et al. [12] extended the use of LSTM networks for PV power production prediction by demonstrating that deep learning models could efficiently forecast short-term power output, providing essential knowledge for grid management. Their findings emphasized the importance of utilizing recurrent neural networks (RNNs) for energy prediction operations, particularly when dealing with the non-linear nature of solar energy generation.

Li et al. [13] used Support Vector Machines (SVM) and an enhanced Dragonfly Algorithm to predict short-term wind power. Their hybrid method outperformed conventional approaches in prediction accuracy, emphasizing the increasing tendency to integrate machine learning with optimization methods for renewable energy prediction. Similarly, Kisvari et al. [14] used Gated Recurrent Neural Networks (GRNN) to enhance wind power forecasting accuracy, tackling difficulties presented by the stochastic nature of wind.

Current innovations in machine learning methods, like deep learning-based ensemble stacking, have also enhanced predicting performance. Khan et al. [15] presented an ensemble method for solar PV prediction that improved prediction accuracy by stacking multiple machine-learning models. Furthermore, Kuzlu et al. [16] used explainable artificial intelligence (XAI) techniques to acquire knowledge of solar PV power production prediction, providing an improved comprehension of the predictive systems' effectiveness and dependability. Table 1 shows the summary table.

Table 1: Summary table

Related Work	Methodology/Model Used	Key Metrics/Findings	Limitations	EGES Advantages
Oskouei et al. (2021) [7]	Decentralized robust-stochastic model	92.9% curtailment reduction, 16.33% cost savings	High complexity, limited adaptability	EGES provides real-time adaptation with KNN-based local processing and dynamic model selection.
Ramesh et al. (2023) [8]	AUTO-encoder NN using RBM feature extraction	Attained important enhancements in error metrics (for example, RMSE: 58.72%)	High RMSE; Computational intricacy with RBM	EGES balances accuracy and computational effectiveness with streamlined feature selection
Sun & You (2021) [9]	ML & Data-Driven Control (DDC)	Highlighted advantages in flexibility and system adaptability	Absence of hybrid ensemble usage for improved precision	EGES utilizes a hybrid ensemble for higher prediction accuracy

Markovics & Mayer (2022) [10]	Kernel Ridge Regression, MLP	Up to 44.6% predict skill over persistence; Hyperparameter tuning crucial	Reliance on predictor set; Prone to overfitting	EGES has superior predictor incorporation and ensemble variety
Vivas et al. (2020) [11]	Comparative evaluation of statistical/ML techniques	Noted decreased errors with hybrid techniques; ML techniques better in accuracy	Time horizon and feature variability difficulties	EGES uses an ensemble that adapts to diverse input data types
Konstantinou et al. (2021) [12]	Stacked LSTM network	Attained low RMSE and stability in short-term predictions	Computational expense of deep networks	EGES attains superior computational effectiveness by incorporating lightweight models
Li et al. (2020) [13]	SVM using enhanced Dragonfly Algorithm	Enhanced accuracy compared to baseline models	Constrained adaptability to novel data without retraining	EGES's ensemble can adapt quicker because of modular updates
Kisvari et al. (2021) [14]	GRU model	GRU surpassed LSTM in predictive accuracy and training time	Noise sensitivity and model tuning necessities	EGES is intended to be robust against data noise
Khan et al. (2022) [15]	Stacked ensemble (ANN, LSTM) incorporated with XGBoost	High accuracy and stability across diverse case studies	High computational request; Deep models are resource-intensive	EGES improves efficiency using a scalable ensemble architecture
Kuzlu et al. (2020) [16]	XAI tools (LIME, SHAP, ELI5) for solar PV prediction	Improved model transparency and important parameter insights	AI models absence of transparency, limiting trust	EGES improves explainability and parameter understanding, enhancing user trust

These previous machine learning techniques for evaluating energy plant efficiency have a research gap in dealing with the dynamic and complicated nature of functional data under a variety of energy plant circumstances. These static designs absent flexibility, leading to lower predictive precision and functional ineffectiveness. The presented EGES fills this research gap by dynamically choosing the most appropriate models for each test sample depending on the local data environment utilizing k-nearest neighbors, thereby enhancing prediction accuracy.

3 Methodology

This section describes the methodology used to assess energy plant efficiency with machine learning models.

The procedure starts with dataset collection and preprocessing, followed by the creation of the EGES, which dynamically chooses models using local data properties. Each model in the ensemble is analyzed in terms of its role in enhancing prediction accuracy.

3.1 Dataset

The dataset used in this study was gathered to assess the efficacy and productivity of energy plants in high-power uses. Between January 2023 and August 2024, it was collected from a variety of energy production facilities in different areas, comprising a thermal power plant, a chemical plant, a hydroelectric plant, and a nuclear power

station. Figure 1 illustrates these various types of energy production systems.

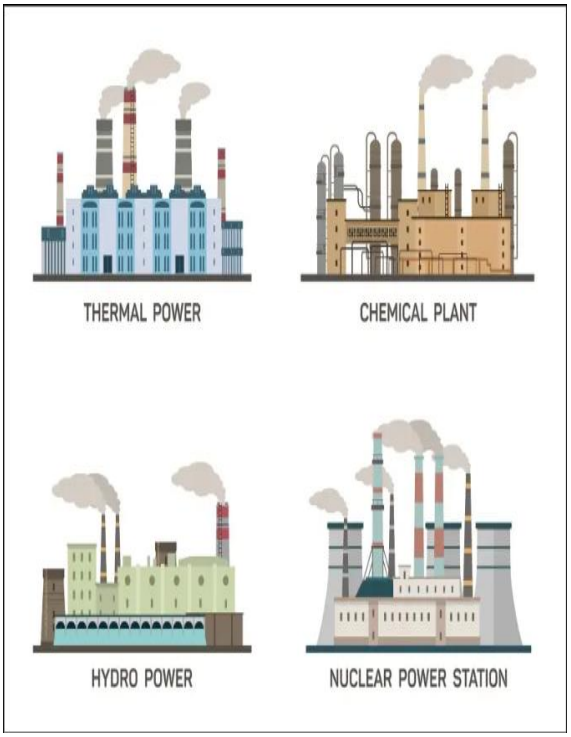

Figure 1: Different types of power plants

Data collection was simplified by direct tracking systems installed at each plant, which tracked functional metrics, power storage effectiveness, and environmental influence data daily. The research also looked into the use of Pumped Hydroelectric Storage (PHS) as a versatile energy storage method for all plant types. PHS enables surplus electricity to be utilized to pump water into elevated reservoirs, and the stored power is then released to produce electricity when demand rises. This approach enables long-term, massive energy storage for conventional and renewable power sources, guaranteeing grid stability and improving plant effectiveness. Figure 2 shows PHS.

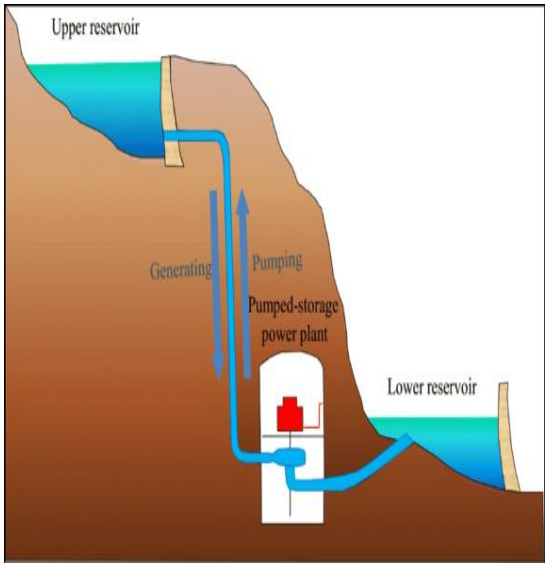

Figure 2: Pumped hydroelectric storage

The main goal of this data gathering was to use machine learning models to evaluate the plants' productivity, cost-efficiency, power storage capacities, and ecological sustainability. Each record in the dataset represents an individual plant's performance indicators, including important operational characteristics. The dataset contains 17 features that are important for assessing energy plants, with a particular emphasis on features that influence energy outcome, functional effectiveness, environmental influence, and expense. These features present an extensive view of the factors impacting plant efficiency and are critical for creating predictive models to categorize plants as having "Good" or "Poor" efficiency.

3.1.1 Attribute description

Plant_ID: A distinct identifier allocated to each energy plant for monitoring and detection reasons.
Energy output (MW): The total quantity of energy produced by the plant, calculated in megawatts (MW). This is a key metric of plant efficiency and production capability.
Efficiency (%): The percentage effectiveness of the plant, which measures how well it transforms fuel into energy. Higher effectiveness is related to reduced fuel utilization and improved efficiency.
Temperature (°C): The plant's operating temperature is calculated in degrees Celsius. The temperature has a significant impact on the plant's effectiveness and upkeep requirements.
Operating hours (hrs/day): The number of hours per day that the plant is functional. This indicates the plant's usage and the length of time it contributes to the energy grid.
Maintenance frequency (times/year): The frequency with which the plant needs upkeep, expressed in terms of times per year. Regular upkeep is essential for guaranteeing the plant's lifespan and reducing failures.

Fault rate (%): The percentage of functional errors or breakdowns in the plant. A higher fault rate suggests possible dependability problems.
Emission level (CO2 tons/year): The quantity of carbon dioxide produced by the plant annually, calculated in tons. Smaller emission rates are essential for ecological compliance and sustainability objectives.
Fuel type: The plant's fuel type, which could be gas, coal, nuclear, or solar. Various fuel kinds have differing effects on emissions, cost, and efficiency.
Power loss (%): The percentage of power lost during the manufacturing or transmission procedure. This indicates ineffectiveness in energy transmission; smaller power loss is preferable.
Downtime (hrs/year): The total quantity of hours per year when the plant is not functional because of maintenance or other problems. Reducing downtime is critical for optimizing plant efficiency.
Cost_per_MW ($): The cost of producing one megawatt of energy in US dollars. This metric measures the financial effectiveness of the plant's functions.
Voltage level (kV): The plant's operational voltage is calculated in kilovolts. Voltage levels influence the transmission effectiveness and distribution of energy.
Load factor (%): The ratio between actual production of energy and maximal potential production. Larger load factors represent a more effective use of the plant's capabilities.
Transformer rating (MVA): The rating of the plant's transformer, calculated in megavolt-amperes (MVA), showing its ability to manage electrical loads.
Cooling method: The plant's cooling system, which can be air or water-based. Cooling techniques are crucial for sustaining functional effectiveness and avoiding overheating.
Plant performance: The machine learning model's target label, which classifies plant performance as Good or Poor using a mixture of effectiveness, emissions, fault rates, and other features.
A sample of 10 records from the dataset is presented below to demonstrate the data's structure and values. These records emphasize the differences in energy generation, fuel type, fault rates, and other performance-associated metrics across various plants.

Table 2: Sample dataset

Plant_ID, Energy_Output (MW), Efficiency (%), Temperature (°C), Operating_Hours (hrs/day), Maintenance_Frequency (times/year), Fault_Rate (%), Emission_Level (CO2 tons/year), Fuel_Type, Power_Loss (%), Downtime (hrs/year), Cost_per_MW ($), Voltage_Level (kV), Load_Factor (%), Transformer_Rating (MVA), Cooling_Method, Plant_Performance
1, 600, 95, 85, 30, 5, 3, 200, Gas, 2.2, 60, 80,000, 130, 85, 170, Air, Good
2, 550, 88, 90, 32, 7, 6, 300, Coal, 3.5, 90, 85,000, 130, 88, 170, Water, Poor
3, 620, 80, 80, 28, 4, 2.5, 90, Nuclear, 1.8, 40, 85,000, 140, 80, 180, Air, Good
4, 580, 92, 95, 31, 6, 5, 280, Gas, 3.5, 70, 98,000, 125, 92, 150, Air, Poor
5, 610, 98, 82, 29, 3, 2.8, 80, Solar, 1.5, 50, 82,000, 150, 97, 170, Water, Good
6, 570, 85, 95, 33, 8, 7, 350, Coal, 5.0, 110, 90,000, 135, 85, 165, Water, Poor
7, 595, 93, 88, 30, 5, 3.5, 220, Gas, 2.5, 70, 99,000, 120, 93, 155, Air, Good
8, 555, 90, 92, 32, 7, 5.5, 320, Coal, 4.0, 80, 96,000, 130, 90, 160, Air, Poor
9, 630, 97, 83, 29, 4, 2.7, 95, Nuclear, 2.0, 45, 84,000, 140, 99, 175, Air, Good
10, 560, 86, 98, 31, 6, 6, 310, Coal, 4.8, 85, 93,000, 125, 87, 150, Water, Poor

Table 2 , shows in Sample dataset. This dataset is intended to assist machine learning systems by enabling for detailed evaluation of energy plant efficiency across a variety of functional and ecological metrics. The dataset's comprehensive features make it easier to train and validate predictive models capable of classifying plant efficiency and suggesting possible regions for improvement.

3.2 Energy guard ensemble selector

The EGES algorithm is intended to dynamically choose the most efficient model from a collection of machine learning algorithms using the local properties of each test instance. The procedure starts with the encoding of categorical features from the training dataset, such as Fuel_Type, Cooling_Method, and Plant_Performance. This is accomplished by label encoding, in which each distinct category is assigned a distinctive integer utilizing Eq. (1).

$$\text{Encoded Value} = f(\text{Category}) \tag{1}$$

For instance, Fuel_Type may be encoded as Gas → 1, Coal → 2, Nuclear → 3, and Solar → 4. After preparing the data, the next step is to train numerous models on the encoded training dataset, including RF, SVM, GBM, KNN, and Logistic Regression. Each model learns to detect trends in the data that correspond to the target feature, Plant_Performance. The training stage, as shown in Eq. (2), is crucial for creating a strong ensemble able to create precise forecasts.

$$\text{Train}(M, x_{train}) \tag{2}$$

Where M denotes the classification methods (RF, SVM, GBM, KNN, and LR) and x_{train} is the encoded training data. Each model M is trained on x_train to learn trends related to the target feature, Plant_Performance.

After the models have been trained, the algorithm determines the chosen parameters, that comprise the number of nearest neighbors k and the Euclidean distance function d. The formula is used to compute the Euclidean distance between the test sample (x_{test}) and the training sample (x_i).

$$d\ (x_{test}, x_i) = \sqrt{\sum_{j=1}^{n}(x_{test,j} - x_{i,j})^2} \quad (3)$$

Where n represents the number of attributes. This calculation enables the algorithm to find the k nearest neighbors, creating a local region that represents the features of comparable instances.

After defining the local region, the next step is to evaluate the model's effectiveness. For each model M_i in the ensemble, the algorithm evaluates its accuracy on the k nearest neighbors utilizing the following formula:

$$\text{Accuracy}\ (M_i) = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, correspondingly. This assessment presents insight into how well each model executes in the setting of the local data. The accuracy scores are stored for comparison, allowing the algorithm to detect which model executes superior for the particular test sample.

After the assessment, the algorithm chooses the model with the highest accuracy score as the best performer. In cases where numerous models achieve the same top score, a tie-breaking solution can be used, considering factors like model complexity or prior efficiency. The selected model is considered the most appropriate for predicting the present test sample.

Lastly, the chosen model is used to forecast the label for the test sample, deciding whether its efficiency is categorized as "Good" or "Poor." The prediction could be formalized as follows:

$$\hat{y} = M_{best}(x_{test}) \quad (5)$$

where $\hat{y}$ is the predicted label and M_{best} is the top-performing model. The outcome is then outputted as the final prediction.

The algorithm follows this procedure for every test sample in the dataset, guaranteeing that each one is evaluated individually corresponding to its particular features. This adaptive chosen technique enhances the overall prediction accuracy, allowing more customized and efficient evaluations of plant performance. The repeated evaluations for all test samples can be described as:

$$Predictions = \{\hat{y}_1, \hat{y}_2, \dots, \hat{y}_m\} \quad for\ each\ x_{test,j} \in D_{test} \quad (6)$$

Here, m denotes the total number of test samples. These equations and procedures form the basis of EGES, providing a dependable framework for predictive modeling in evaluating energy plant performance.

The EGES algorithm scales with bigger datasets and higher feature dimensionality by employing a KNN method, which decreases computational burden by selecting only the closest samples for model selection. However, as the dataset grows in size and dimensionality, computing pairwise distances and training numerous models becomes more time-consuming. Despite this, EGES remains effective by restricting the search space; however, performance may suffer in massive, real-time energy applications because of the increased computational load.

Algorithm 1 outlines the suggested EGES algorithm.

Algorithm 1: EGES

Input : x_train, x_test, M = {RF, SVM, GBM, KNN, LR}, k, Euclidean Distance d

Output : Predicted label for x_test

Step 1 : Encode categorical features in x_train:
- **Fuel_Type:** Encode (Gas = 0, Coal = 1, Nuclear = 2, Solar = 3)
- **Cooling_Method:** Encode (Air = 0, Water = 1)
- **Plant_Performance:** Encode (Poor = 0, Good = 1)

Step 2 : Train models RF, SVM, GBM, KNN, LR on x_train

Step 3 : Set parameters: k, d

Step 4 : For each test sample x_test:

Step 5 : **Local Region Definition**
For each sample x_i in x_train:
- Calculate Euclidean distance d (x_test, x_i)

Choose k nearest neighbors from x_train using the smallest Euclidean distances

Step 6 : **Model Performance Assessment (utilizing accuracy)**
For each model $M_i \in$ {RF, SVM, GBM, KNN, LR}:
Assess the accuracy of M_i on the k nearest neighbors
Store accuracy score of M_i

Step 7 : **Model Selection**
Choose the best-performing model with the maximum accuracy score.

Step 8 : **Prediction**
Utilize the chosen model to predict the label for x_test

Output the forecasted label for x_test (Poor or Good)

Step 9 : Repeat for all test samples.

3.2.1 RF

RF is an ensemble learning technique that constructs numerous decision trees and then combines their predictions to enhance classification accuracy. RF operates by training each tree on a randomly selected subset of the data and attributes, decreasing variability and preventing overfitting. RF was selected for EGES because of its capacity to handle large datasets and nonlinear correlations between features. In this research, RF helps the model ensemble by providing excellent predictive abilities, especially when dealing with intricate relationships between variables like temperature, fault rates, and the production of energy.

3.2.2 SVM

The SVM is an effective classifier that seeks to identify the best hyperplane that divides various classes in the dataset. SVM performs well in high-dimensional spaces and is useful for both linear and nonlinear classification activities. In EGES, SVM aids in differentiating between "good" and "poor" operating plants by evaluating the complicated relationship between plant effectiveness, functioning hours, and downtime. The model is especially helpful in situations where the classes are not linearly separable, utilizing kernel functions for enhanced efficiency.

3.2.3 GBM

GBM is another ensemble technique that constructs models sequentially, with each model attempting to right the flaws of the previous one. GBM is well-known for its high forecasting accuracy, particularly in situations involving intricate relationships between features. In the setting of this research, GBM improves EGES efficiency by concentrating on decreasing error in forecasting plant efficiency using variables such as emission stages, service frequency, and fault rates. GBM contributes to the ensemble through its capability to decrease bias and enhance generalization.

3.2.4 KNN

KNN is a non-parametric algorithm that categorizes data points according to the majority class of their nearest neighbors. KNN is especially efficient when local data points exhibit comparable trends, rendering it an ideal candidate for EGES. By assessing the local neighborhood of each test sample, KNN aids in the identification of comparable plants using features such as fuel type, power loss, and downtime, enhancing the model's capacity to forecast plant efficiency in particular situations. KNN's ease and efficiency in local region classification render it a useful member of the ensemble.

3.2.5 LR

LR is a linear model utilized to perform binary classification tasks. It forecasts the likelihood of an event happening, like whether a plant will execute "good" or "poor." In EGES, LR is used to manage cases where the correlation between variables is linear. For instance, LR is effective at detecting efficiency patterns using energy results and cost per megawatt. Despite its simplicity, LR contributes to the ensemble by presenting baseline predictions that could be improved by more complicated models such as RF and GBM.

The EGES dynamically chooses models using local data features, thereby improving prediction accuracy for energy plant efficiency classification. EGES enhances prediction dependability by utilizing a various set of machine learning models, each customized to various data trends, guaranteeing that the most effective model is used for each test case.

Model selection procedure

EGES' model selection process dynamically compares the accuracy scores of numerous classifiers (RF, SVM, GBM, KNN, and LR) for each test sample. If multiple models produce similar accuracy scores, a tie-breaking strategy is used to determine the best model. The tie-breaking procedure adheres to a predefined criterion hierarchy: first, the model with the smallest computational complexity (especially simpler models to decrease overfitting risks) is selected. If there is still a tie, the model with the best historical performance on comparable datasets is chosen. In cases where the models have comparable performance records, the model with the shortest runtime is chosen to maximize effectiveness for real-time predictions. This structured tie-breaking guarantees that the final model selection is not only the most precise but also the best fit for operational limitations, thus enhancing the overall prediction procedure.

Model interpretability and computational complexity

The EGES algorithm is highly efficient, but computationally complex because of the dynamic selection procedure, especially in calculating the Euclidean distances for k-nearest neighbors, which scales with O (n.m), where n is the number of training samples and m is the feature count. This complexity emphasizes the trade-off between accuracy and possibility in real-time, massive applications. EGES also integrates model interpretability through feature importance assessment using ensemble models such as Random Forest and GBM. Such interpretability is essential for energy sector stakeholders because it allows for transparency and comprehension of decisions, especially those involving key features such as Fuel_Type and Cooling_Method, which have a direct impact on predictions. This balance of

computational effectiveness and interpretability distinguishes EGES as a useful yet insightful tool for evaluating energy efficiency.

Figure 3 displays the flow diagram of the EGES algorithm.

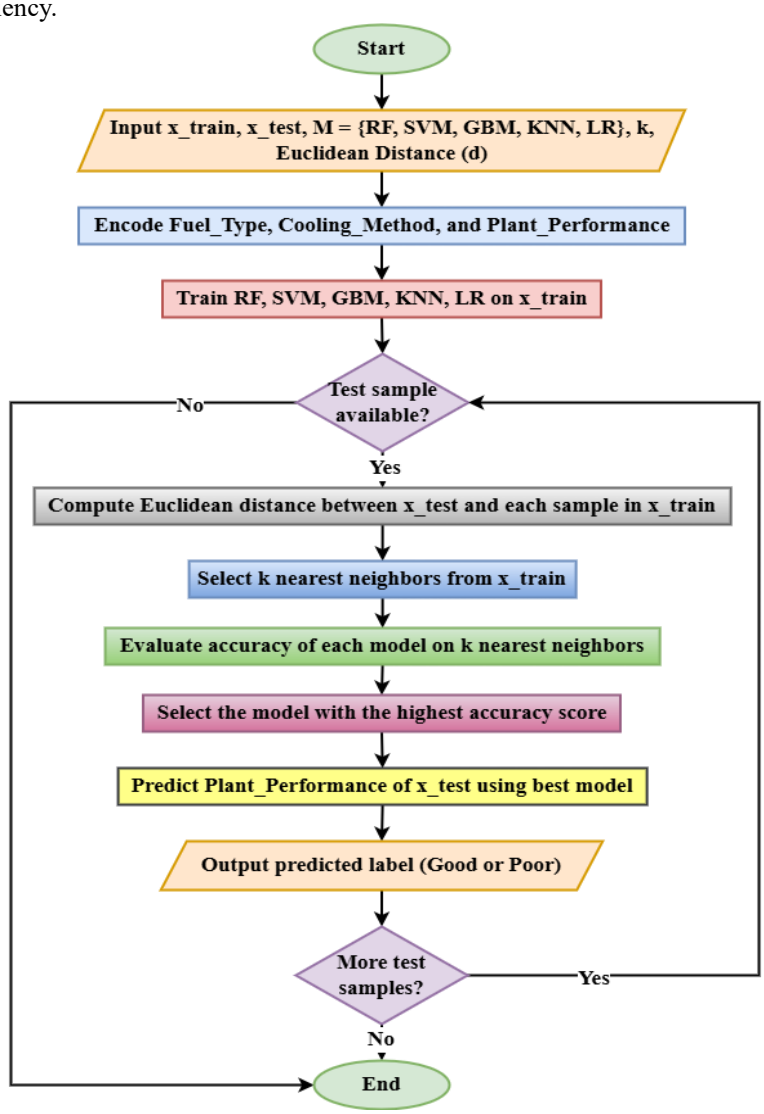

Figure 3: Flow diagram of EGES algorithm

4 Experimental results and discussions

This section provides the experimental findings of the suggested EGES algorithm and compares its efficacy to five well-known machine learning classifiers: RF, SVM, GBM, KNN, and Logistic Regression. The EGES algorithm was written in Java and implemented with the Weka machine learning tool, which makes use of Weka's library of classifiers and distance functions to train and evaluate models efficiently. Weka was selected because of its comprehensive assistance for a broad range of machine learning algorithms and its capacity to manage intricate data preprocessing, model evaluation, and performance measurement tasks seamlessly.

To guarantee a balanced dataset for training and assessment, the Synthetic Minority Over-sampling Technique (SMOTE) was used to correct class imbalances by efficiently augmenting minority class samples. EGES classifier hyperparameters were improved utilizing grid search and 5-fold cross-validation. RF was tuned for 100 trees and max depth 15, SVM for RBF kernel and C=1.0, GBM for learning rate 0.1, 100 estimators and depth 3, KNN for k=5 with Euclidean distance, and LR for L2 penalty with liblinear solver. These tactics guaranteed consistent performance across test cases.

EGES' effectiveness was evaluated using numerous important metrics, including accuracy, precision, recall, F1-score, and MCC. These metrics offer an extensive comprehension of the classification models' efficiency, providing insights into both predictability and dependability.

Accuracy: This metric calculates the percentage of correct results for all cases evaluated. It is a basic indicator of a classifier's overall efficacy, which includes both true

positives and true negatives. The formula for accuracy is shown in Eq. (4).

Precision: Precision is the percentage of true positives among those that were predicted to be positive. It is especially important in situations where the cost of false positives is high. Precision is determined as follows:

$$Precision = \frac{TP}{TP + FP} \quad (7)$$

High precision means that when the classifier forecasts a positive class, it is likely to be correct.

Recall: Recall, also known as sensitivity or true positive rate, is a measure of how many actual positives the classifier accurately detects. It is critical in circumstances where losing a positive case is costly. The recall is provided by:

$$Recall = \frac{TP}{TP + FN} \quad (8)$$

A high recall indicates that the classifier accurately identifies the majority of the actual positive cases.

F1-score: The F1-score balances precision and recall, which is especially helpful when the dataset is imbalanced. The harmonic mean of precision and recall is calculated as follows:

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (9)$$

A high F1 score signifies that the classifier performs well in terms of precision and recall.

MCC: MCC is a more extensive metric that takes into account all four categories (TP, TN, FP, and FN). It is particularly helpful when dealing with imbalanced datasets. It is calculated using the following formula:

$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (10)$$

An MCC value near 1 denotes a strong positive correlation between predicted and actual classifications.

The performance metrics chosen for EGES, such as accuracy, precision, recall, F1-score, and MCC, are essential in assessing energy plant efficiency. Accuracy measures overall correctness, whereas precision and recall help to reduce costly false positives and negatives. The F1-score balances these metrics, resulting in a comprehensive evaluation. MCC provides a balanced measure that takes into account all types of prediction errors, making it particularly helpful for imbalanced datasets. While these metrics are focused on classification, considering economic effects could improve the assessment by reflecting the operational expenses and effectiveness losses related to inaccurate predictions.

Table 3, displays the comparative performance of EGES against RF, SVM, GBM, KNN, and LR:

Table 3: Performance metrics comparison

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	MCC (%)
RF	88.5	88.2	89.5	88.8	85.5
SVM	89.0	86.5	87.7	87.1	83.0
GBM	91.2	89.0	88.5	89.7	87.0
KNN	88.5	87.0	86.2	86.6	81.5
LR	87.8	85.3	86.7	86.0	81.0
EGES	93.5	91.5	92.7	92.1	90.0

The EGES algorithm surpasses all other classifiers on all performance metrics. EGES, in particular, attained the highest accuracy of 93.5%, which is substantially higher than GBM, the closest competitor, who attained 91.2%. This increase in accuracy shows the efficacy of EGES in correctly categorizing test samples using the local region determined by the nearest neighbors and leveraging model selection depending on accuracy evaluation.

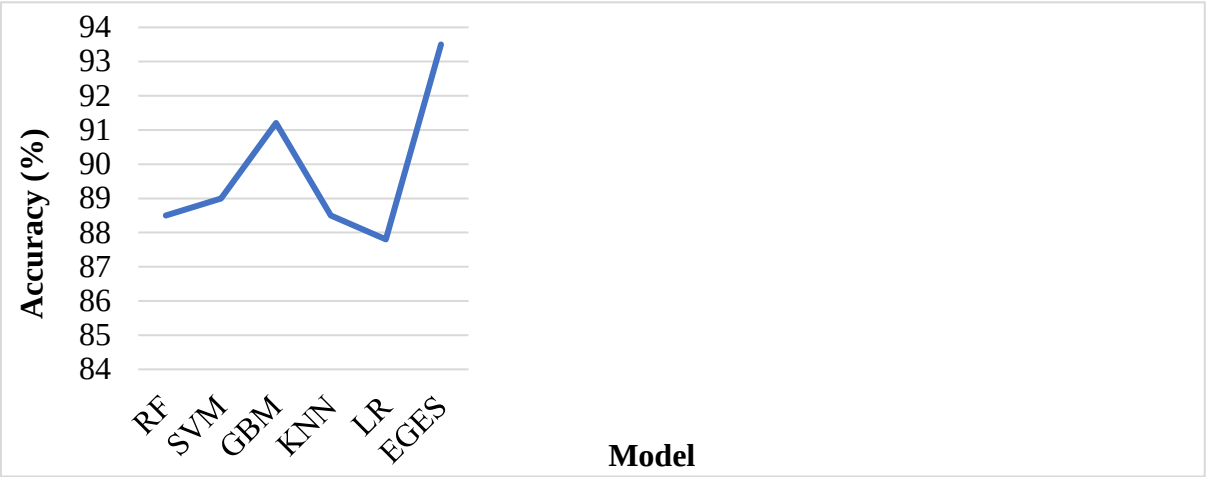

Figure 4: Accuracy comparison

Figure 4 shows a line chart comparing the accuracy of EGES to the other classifiers. The chart emphasizes EGES' better efficiency, demonstrating its position as the most precise model. EGES uses k-nearest neighbor selection and model accuracy evaluation to improve its predictions and surpass conventional machine learning models such as RF, SVM, and GBM. This demonstrates EGES' superiority in determining the most effective prediction model, resulting in the highest accuracy.

In terms of precision, EGES also outperforms the competition with a score of 91.5%, as demonstrated in Table 2 and Figure 5. Precision is critical for reducing false positives, and EGES's higher precision score suggests that it makes fewer erroneous positive predictions than other models. This precision benefit comes from the EGES algorithm's dynamic selection of the best-performing model for each test sample, which enables it to achieve more precise classification results.

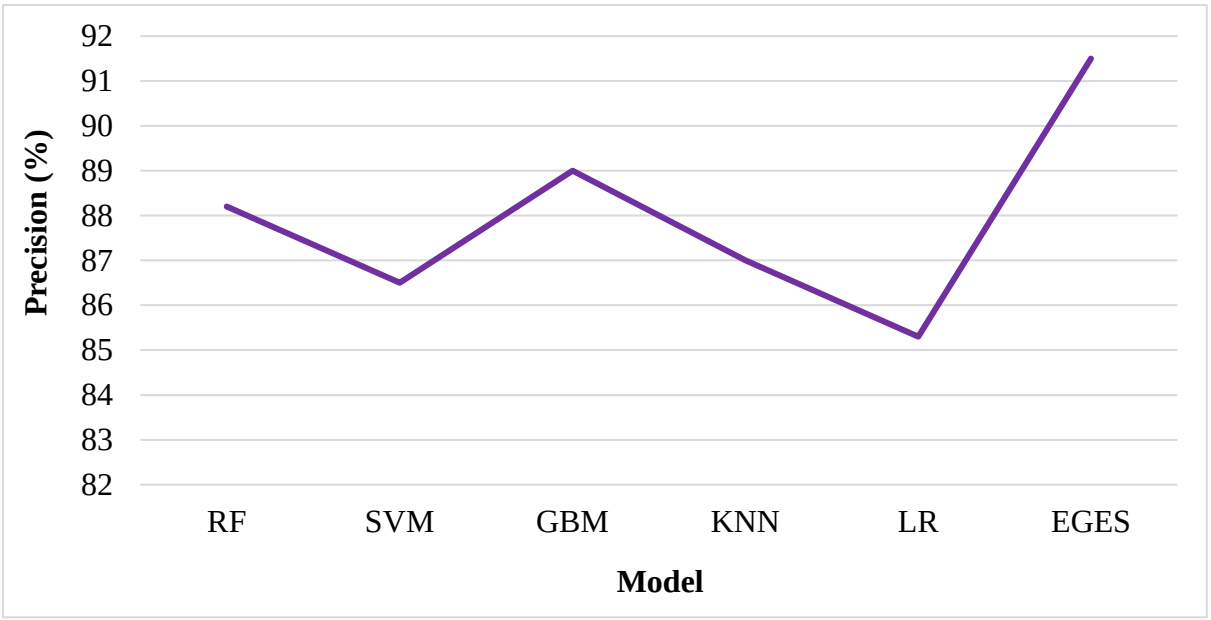

Figure 5: Precision comparison

Figure 5 shows a line chart with the precision values for the classifiers, demonstrating EGES' superiority once again. Its capability to provide high precision, particularly when compared to models such as SVM and LR, shows the strength of EGES' ensemble method. This confirms that the dynamic selection of classifiers using accuracy results in not only higher precision but also more dependable predictions in general.

When assessing recall, EGES continues to surpass the other models, with a score of 92.7%, as shown in Figure 6. The recall is critical for detecting all pertinent instances of the target class, and a higher recall score signifies that EGES correctly detects a greater proportion of true positives than other models. This makes EGES especially appropriate for applications where detecting positive instances is critical.

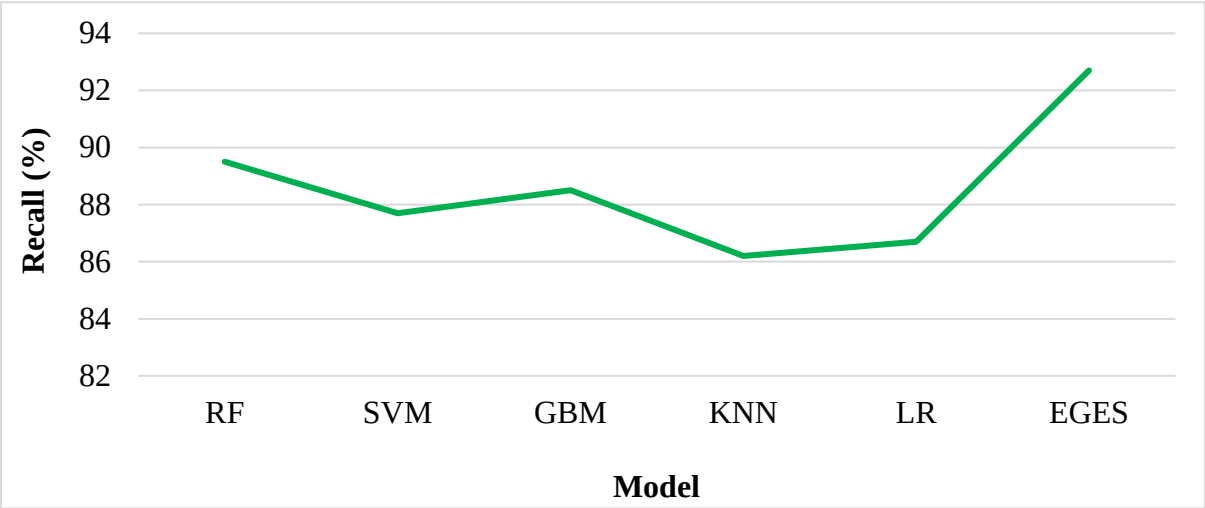

Figure 6: Recall Comparison

Figure 6 depicts the recall comparison among the classifiers, with EGES emerging as the leader. This demonstrates EGES's ability to identify pertinent instances and ensure extensive coverage of the target attribute. The integration of k-nearest neighbor selection and the utilization of accuracy for model assessment allows EGES to attain higher recall than models like RF and KNN.

In terms of the F1-score, which balances precision and recall, EGES has the highest score (92.1%). As illustrated in Figure 7, this result shows that EGES strikes an excellent balance between precision and recall, operating well in both dimensions. The F1-score comparison validates EGES' resilience in guaranteeing high classification effectiveness while reducing faults.

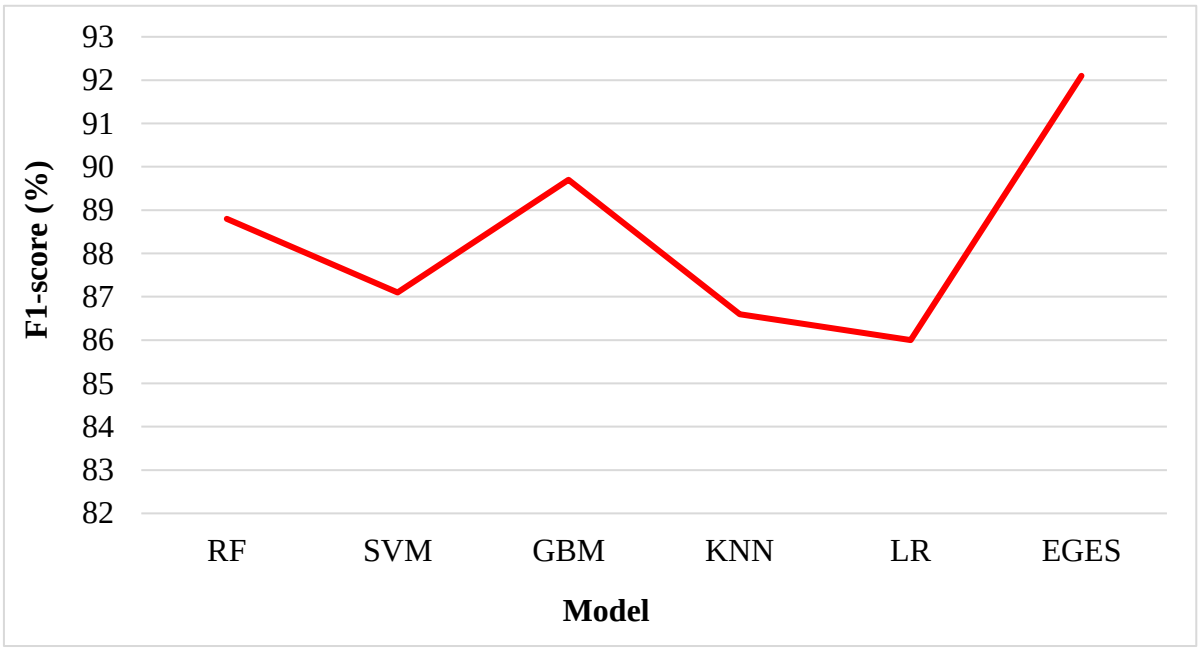

Figure 7: F1-score Comparison

Figure 7 shows a line chart comparing F1 scores, with EGES once again outperforming the other classification methods. The balance between precision and recall shows the algorithm's capacity to improve prediction performance without sacrificing one metric for the other.

Lastly, the Matthews Correlation Coefficient (MCC) is calculated, which provides a more dependable measure of classification efficiency, particularly in the presence of imbalanced data. EGES has the highest MCC score of 90.0%, as illustrated in Figure 8. The higher MCC score suggests that EGES presents a more balanced and accurate classification, taking into account both true and false positives and negatives.

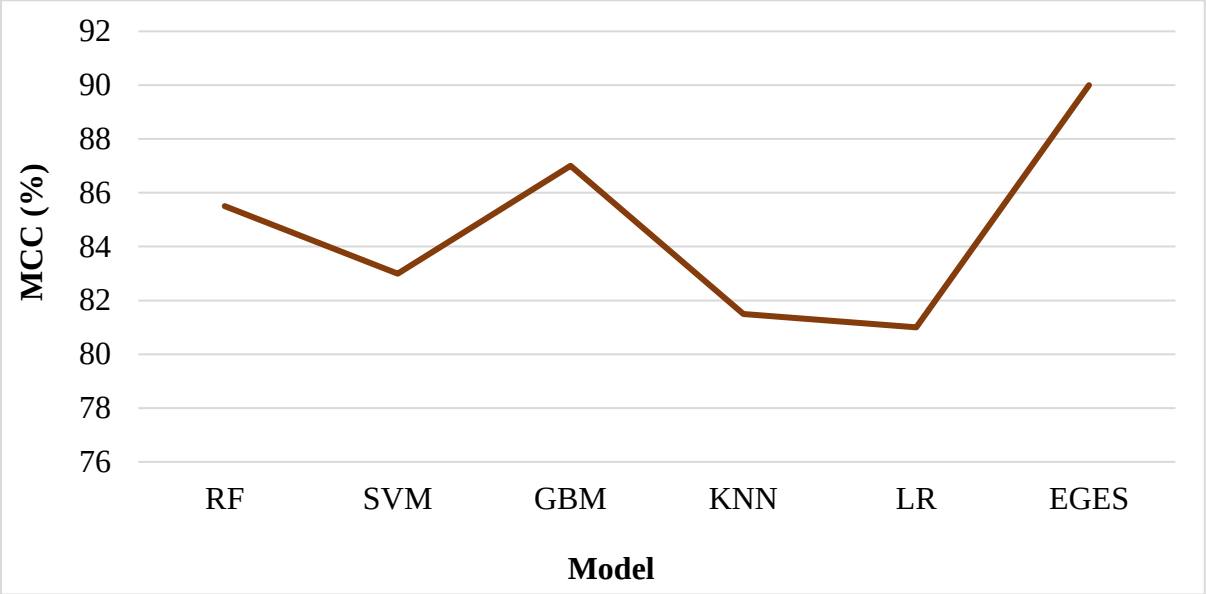

Figure 8: MCC Comparison

Figure 8 shows EGES' superiority in terms of MCC, cementing its position as the best-performing model in this study. The MCC score highlights EGES's ability to deal with imbalanced datasets and provide dependable classification outcomes across different metrics.

Overall, the experimental findings clearly show that the EGES algorithm outperforms other classifiers. EGES consistently surpasses conventional machine learning models like RF, SVM, GBM, KNN, and LR on all performance metrics, including accuracy, precision, recall, F1-score, and MCC. The use of k-nearest neighbor selection, accuracy-based model assessment, and dynamic model selection improves EGES's resilience and accuracy in forecasting plant performance. These findings justify the use of EGES as an efficient and dependable classification algorithm, especially in applications requiring accurate and precise predictions.

Error analysis

EGES error analysis shows that poor performance is most common when data is sparse or plant types are highly imbalanced, with certain classes underrepresented. These errors are most evident when the model is unable to differentiate between closely related plant performance categories, particularly in situations where the feature set lacks enough variation or the KNN model's chosen k is not optimized. Furthermore, performance degradation occurs when certain parameter settings, like the distance function or the number of neighbors (k), do not correspond to the underlying data distribution. Evaluating these error-prone cases reveals important information about potential model constraints, emphasizing the significance of modifying hyperparameters and guaranteeing balanced, comprehensive data for more reliable predictions.

Discussion

The experimental findings show that EGES surpasses conventional models like RF, SVM, GBM, KNN, and LR in all important metrics, with the highest accuracy (93.5%), precision (91.5%), recall (92.7%), F1-score (92.1%), and MCC (90.0%). EGES outperforms the state-of-the-art (SOTA) techniques reviewed due to its dynamic model selection strategy and k-nearest neighbor (KNN)-based local data adaptation, which allow it to tailor predictions to the unique characteristics of each test sample. Unlike conventional models, which depend on global patterns learned during training, EGES dynamically assesses and chooses the most efficient model depending on localized accuracy, guaranteeing reliable predictions even in intricate, high-power application settings. Furthermore, KNN-driven local region formation reduces overgeneralization by concentrating on data subsets with similar characteristics, which improves precision and adaptability. This design contrasts with the static nature of traditional SOTA techniques, which frequently fail with the fluctuating parameters found in energy plant performance evaluations. By tackling these difficulties and offering high accuracy under dynamic conditions, EGES shows its novelty and practicality for energy system predictive modeling.

5 Conclusion

The EGES algorithm implemented in this study outperformed conventional models like RF, SVM, GBM, KNN, and LR in terms of plant performance classification and prediction. By its dynamic model selection and k-nearest neighbor method, EGES consistently attained higher accuracy, precision, recall, F1-score, and MCC across all assessments, as executed in Java and Weka. Its

resilient efficiency demonstrates the algorithm's possibility for wider use beyond plant performance, implying that future research could include adapting EGES to other areas like healthcare, finance, or e-commerce, where accurate classification is required. Future work on EGES could concentrate on tackling dataset imbalance, especially in terms of "Good" versus "Poor" performance labels, by incorporating methods like SMOTE (Synthetic Minority Over-sampling Technique) to improve model resilience. Furthermore, integrating deep learning techniques like neural networks or reinforcement learning methods could enhance EGES' flexibility in dynamic and fluctuating settings. These sophisticated methods could allow EGES to effectively manage intricate, non-linear relationships and learn from real-time data feedback, possibly boosting scalability and accuracy in real-world energy applications.

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FD3QN: A Federated Deep Reinforcement Learning Approach for Cross-Domain Resource Cooperative Scheduling in Hybrid Cloud Architecture

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To address the challenge of insufficient computing power in multi-access edge computing (MEC) servers caused by highly dynamic service requests and uneven service distribution in vehicular networks, this paper proposes a hybrid multi-server MEC architecture that leverages both fixed road-side units (RSUs) and mobile unmanned aerial vehicles (UAVs). We introduce the FD3QN algorithm, which integrates federated learning and deep reinforcement learning, to minimize the weighted sum of service latency and energy consumption. Specifically, the MATD3 algorithm is employed for safe and efficient UAV trajectory planning in the offloading decision process. For resource allocation, we embed vertical federated learning into the D3QN network to enable cross-domain resource cooperative scheduling. A decentralized federated aggregation framework is utilized to maintain a global model for optimizing resource allocation in a collaborative and privacy-preserving manner. The proposed algorithm jointly optimizes transmission power, computing, and storage resources. Extensive simulations are conducted to evaluate the performance of FD3QN in a realistic vehicular network environment with varying numbers of vehicles and task arrivals. The results demonstrate that FD3QN outperforms benchmark algorithms, achieving an 11.37% and 12.06% reduction in system cost compared to the FDDQN algorithm in scenarios with 8 and 12 vehicles, respectively. Moreover, FD3QN exhibits a 25% decrease in average service latency and a 15% improvement in energy efficiency compared to traditional deep reinforcement learning approaches. The proposed algorithm also maintains a high task completion rate of over 98% under dynamic network conditions. These findings validate the strong model generalization ability of FD3QN in the dynamic vehicular networking environment and highlight its practicality for real-world deployment. This study provides novel insights into the development of intelligent transportation systems and edge computing paradigms.

Povzetek: V prispevku je opisan FD3QN, napreden pristop federativnega globokega okrepljenega učenja za sodelovalno razporejanje virov v hibridnih oblačnih arhitekturah. Algoritem zmanjšuje zakasnitve in porabo energije v inteligentnih transportnih sistemih.

1 Introduction

The rapid advancement of intelligent transportation systems (ITS) has revolutionized the way we perceive and interact with modern transportation networks. With the proliferation of connected and autonomous vehicles (CAVs), the demand for computation-intensive and delay-sensitive applications has escalated significantly [1]. However, the resource-constrained nature of vehicular users poses a formidable challenge in meeting the stringent requirements of these applications [2]. To address this issue, multi-access edge computing (MEC) has emerged as a promising paradigm, bringing computation and storage resources closer to the edge of the network [3]. By leveraging the proximity of MEC servers to vehicular users, the latency and network congestion associated with centralized cloud computing can be effectively mitigated [4].

Furthermore, the integration of unmanned aerial vehicles (UAVs) into the MEC framework has opened up new avenues for enhancing the performance of ITS [5]. UAVs can act as aerial MEC servers, providing flexible and on-demand computing resources to vehicular users [6]. The mobility and line-of-sight (LoS) communication links offered by UAVs enable them to dynamically adjust their positions and serve as relay nodes, extending the coverage

and capacity of the vehicular network [7]. Moreover, the collaboration between ground MEC servers and UAV-assisted MEC servers forms a hybrid multi-server architecture, which can efficiently handle the diverse computational requirements of vehicular applications [8]. However, the deployment of a hybrid multi-server MEC architecture in ITS presents several challenges. The heterogeneous nature of vehicular users, with varying mobility patterns and resource demands, necessitates efficient resource allocation and computation offloading strategies [9]. Additionally, the dynamic and uncertain wireless network conditions, coupled with the limited battery life of UAVs, further complicate the decision-making process [10]. To tackle these challenges, advanced techniques such as deep reinforcement learning (DRL) have gained significant attention [11]. DRL combines the power of deep neural networks with reinforcement learning, enabling agents to learn optimal policies through interaction with the environment [12].

In this article, we propose a novel framework for hybrid multi-server computation offloading in UAV-assisted vehicular networks based on federated deep reinforcement learning (FDRL). The proposed framework leverages the distributed learning capabilities of FDRL to enable collaborative and efficient offloading decisions among vehicular users, ground MEC servers, and UAV-assisted MEC servers. By exploiting the local observations and experiences of individual agents, FDRL allows for the development of personalized offloading policies while preserving the privacy of sensitive data [13]. The framework aims to minimize the overall latency and energy consumption of vehicular users while ensuring the stability and scalability of the network.

The main contributions of this article are as follows:

- We formulate the computation offloading problem in a hybrid multi-server MEC architecture for ITS, considering the heterogeneous requirements of vehicular users and the dynamic network conditions.
- We propose an FDRL-based approach to solve the formulated problem, enabling collaborative and efficient offloading decisions among the entities in the network.
- We conduct extensive simulations to evaluate the performance of the proposed framework and compare it with state-of-the-art offloading strategies.

The remainder of this article is organized as follows. Section II provides an overview of the related work on computation offloading in vehicular networks and the application of DRL in MEC. Section III presents the system model and problem formulation. The proposed FDRL-based offloading framework is detailed in Section IV. Section V discusses the simulation results and performance evaluation. Finally, Section VI concludes the article and outlines future research directions.

2 System model

In this section, we present the system model for the proposed hybrid multi-server MEC architecture in UAV-assisted vehicular networks. We consider a novel network architecture that leverages the collaborative computing capabilities of road-side units (RSUs) and unmanned aerial vehicles (UAVs) to support computation offloading for vehicular users [14]. The system model encompasses the network architecture and the binary offloading model, which form the foundation for the development of the FDRL-based offloading framework. Table 1 shows related works on computation offloading in vehicular networks

Table 1: Comparison of related works on computation offloading in vehicular networks.

Work	Computing Resources	Optimization Objectives	Solution Method	Federated Learning	Comparison with Proposed Work
[1]	RSU	Latency	DQN	No	Single-server, latency only
[2]	RSU, Cloud	Energy	DDPG	No	Multi-server, energy only
[3]	RSU, UAV	Latency, Energy	A3C	No	Multi-server, no FL
[4]	RSU, Cloud	Latency, Energy	DQN, DDPG	No	Multi-server, no FL
[5]	UAV	Latency, Energy	Q-learning	No	Single-server, no FL
[6]	UAV	Energy	DDPG	No	Single-server, energy only
[7]	UAV	Energy	Lyapunov	No	Single-server, energy only
[8]	RSU, Cloud	Latency, Energy	DQN	No	Multi-server, no FL

[9]	UAV	Latency, Energy	DRL	No	Single-server, no FL
[10]	UAV	QoE	DQN	No	Single-server, QoE
[11]	UAV	Latency, Energy	DRL	No	Single-server, no FL
[12]	RSU, Cloud	Latency, Energy	DQN	No	Multi-server, no FL
[13]	RSU, Cloud	Latency, Energy	DDPG	Yes	Multi-server, FL
[14]	RSU, UAV, Cloud	Latency, Energy, Cost	DQL	Yes	Multi-server, FL, cost
Proposed	RSU, UAV	Latency, Energy	MATD3, FUD3QN	Yes	Hybrid multi-server, FL

2.1 Network architecture and binary offloading model

The considered network architecture, as depicted in Figure 1, consists of a typical scenario with one RSU and multiple UAVs serving as MEC servers. The RSU is deployed along the roadside and is equipped with substantial computing resources to handle computation-intensive tasks [15]. On the other hand, the UAVs are strategically positioned in the air to provide flexible and on-demand computing services to vehicular users [16]. The UAVs can dynamically adjust their locations based on the distribution and requirements of the vehicular users, ensuring optimal coverage and quality of service [17].

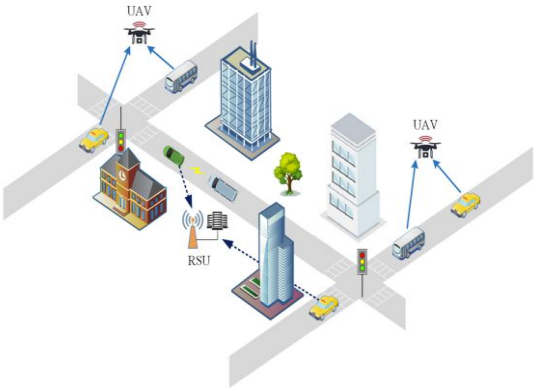

Figure 1: System model of UAV-assisted vehicular networks in a hybrid multi-server MEC architecture.

In the proposed system model, vehicular users have the option to execute their computation tasks locally or offload them to either the RSU or one of the UAVs for remote execution. The decision to offload a task is based on a binary offloading model, where each task is considered as an indivisible unit and can be either processed locally or offloaded to a single MEC server [18]. The binary offloading model simplifies the decision-making process and reduces the complexity of task partitioning and synchronization [19].

Let $\mathcal{U} = \{u_1, u_2, \ldots, u_N\}$ denote the set of vehicular users in the network, where N is the total number of users. Each user u_i generates a sequence of computation tasks over time, represented by $\mathcal{T}_i = \{t_{i,1}, t_{i,2}, \ldots, t_{i,M}\}$, where M is the number of tasks generated by user u_i. Each task $t_{i,j}$ is characterized by its input data size $d_{i,j}$ (in bits) and the required computing resources $c_{i,j}$ (in CPU cycles)

The vehicular users can communicate with the RSU and UAVs through wireless communication links, as shown in Figure 1. The communication links between the users and the RSU are established using dedicated short-range communication (DSRC) technology, which provides reliable and low-latency communication in vehicular environments [20]. On the other hand, the communication links between the users and the UAVs are established using cellular networks, such as LTE or 5G, which offer wider coverage and higher data rates [21].

The decision to offload a task $t_{i,j}$ is determined by the binary offloading variable $x_{i,j} \in \{0,1\}$, where $x_{i,j} = 0$ indicates local execution and $x_{i,j} = 1$ indicates offloading to either the RSU or a UAV. The offloading decision for each task is made based on various factors, such as the task characteristics, the available computing resources, the communication link quality, and the energy consumption [22].

The objective of the proposed FDRL-based offloading framework is to minimize the overall latency and energy consumption of vehicular users while ensuring the stability and scalability of the network. The framework takes into account the heterogeneous requirements of vehicular users, the dynamic network conditions, and the collaborative computing capabilities of the RSU and UAVs to make optimal offloading decisions [24].

In the following sections, we will delve into the details of the FDRL-based offloading framework, including the problem formulation, the learning algorithm, and the performance evaluation.

2.2 UAV trajectory planning

In the UAV trajectory planning phase, the UAVs are required to take off from fixed ground points and adaptively fly to designated points in the air [25]. The trajectory planning problem aims to determine the optimal

flight paths for the UAVs, considering various constraints such as energy consumption, flight time, and collision avoidance.

Let $\mathcal{V} = \{v_1, v_2, \ldots, v_K\}$ denote the set of UAVs in the network, where K is the total number of UAVs. Each UAV v_k has an initial position $\mathbf{p}_k^0 = (x_k^0, y_k^0, z_k^0)$ on the ground and a designated hovering position $\mathbf{p}_k^h = (x_k^h, y_k^h, z_k^h)$ in the air. The trajectory of UAV v_k is represented by a sequence of positions $\mathbf{p}_k(t) = (x_k(t), y_k(t), z_k(t))$, where $t \in [0, T]$ is the time variable and T is the total flight time.

The trajectory planning problem can be formulated as an optimization problem, with the objective of minimizing the total energy consumption of the UAVs while satisfying the flight time and collision avoidance constraints. The energy consumption of UAV v_k along its trajectory $\mathbf{p}_k(t)$ can be expressed as:

$$E_k = \int_0^T P_k\left(\mathbf{p}_k(t), \mathbf{v}_k(t)\right)dt, \tag{1}$$

where $P_k(\mathbf{p}_k(t), \mathbf{v}_k(t))$ is the power consumption of UAV v_k at position $\mathbf{p}_k(t)$ and velocity $\mathbf{v}_k(t)$.

The flight time constraint ensures that each UAV reaches its designated hovering position within the specified time limit T:

$$\| \mathbf{p}_k(T) - \mathbf{p}_k^h \| \leq \varepsilon, \quad \forall k \in \mathcal{V}, \tag{2}$$

where ε is a small tolerance threshold.

The collision avoidance constraint guarantees a minimum separation distance $d_{\min}$ between any two UAVs at all times:

$$\| \mathbf{p}_k(t) - \mathbf{p}_{k'}(t) \| \geq d_{\min}, \quad \forall k, k' \in \mathcal{V}, k \neq k', \forall t \in [0, T]. \tag{3}$$

Once the UAVs reach their designated hovering positions, they act as MEC servers for the vehicular users. The hovering UAVs provide computing resources to the users, enabling them to offload their computation tasks for remote execution. The stable hovering positions of the UAVs ensure reliable communication links and efficient computation offloading services.

The trajectory planning problem can be solved using various optimization techniques, such as convex optimization, dynamic programming, or meta-heuristic algorithms. The optimal trajectories obtained from the planning phase are then used as inputs to the FDRL-based offloading framework, which determines the optimal offloading decisions for the vehicular users.

In the next section, we will present the problem formulation for the computation offloading problem in the hybrid multi-server MEC architecture, considering the network architecture, binary offloading model, and UAV trajectory planning.

2.3 Resource allocation

In the resource allocation phase, we present the communication model, computation model, and energy consumption model to capture the essential aspects of the hybrid multi-server MEC architecture in UAV-assisted vehicular networks.

2.3.1 Communication model

The communication model characterizes the data transmission process between the vehicular users and the MEC servers (RSU and UAVs). Let $R_{i,j}^r$ and $R_{i,j}^{u_k}$ denote the achievable data rates for offloading task $t_{i,j}$ from user u_i to the RSU and UAV v_k, respectively. The data rates can be expressed using the Shannon-Hartley theorem [26]:

$$R_{i,j}^r = B^r \log_2\left(1 + \frac{P_i^r G_{i,j}^r}{\sigma^2}\right), \tag{4}$$

$$R_{i,j}^{u_k} = B^{u_k} \log_2\left(1 + \frac{P_i^{u_k} G_{i,j}^{u_k}}{\sigma^2}\right), \tag{5}$$

where B^r and B^{u_k} are the channel bandwidths, P_i^r and $P_i^{u_k}$ are the transmission powers, $G_{i,j}^r$ and $G_{i,j}^{u_k}$ are the channel gains, and σ^2 is the noise power.

The transmission delay for offloading task $t_{i,j}$ to the RSU and UAV v_k can be calculated as:

$$D_{i,j}^r = \frac{d_{i,j}}{R_{i,j}^r}, \tag{6}$$

$$D_{i,j}^{u_k} = \frac{d_{i,j}}{R_{i,j}^{u_k}}. \tag{7}$$

2.3.2 Computation model

The computation model describes the processing of tasks at the vehicular users and MEC servers. Let f_i^l denote the local computing capability (in CPU cycles per second) of user u_i. The local execution time for task $t_{i,j}$ can be expressed as

$$T_{i,j}^l = \frac{c_{i,j}}{f_i^l}. \tag{8}$$

Similarly, let f^r and f^{u_k} represent the computing capabilities of the RSU and UAV v_k, respectively. The execution time for task $t_{i,j}$ offloaded to the RSU and UAV v_k can be calculated as:

$$T_{i,j}^r = \frac{c_{i,j}}{f^r}, \tag{9}$$

$$T_{i,j}^{u_k} = \frac{c_{i,j}}{f^{u_k}}. \tag{10}$$

2.3.3 Energy consumption model

The energy consumption model captures the energy consumed by the vehicular users for task execution and data transmission. The energy consumption for local execution of task $t_{i,j}$ can be expressed as:

$$E_{i,j}^{l} = \kappa \left(f_i^{l}\right)^2 c_{i,j}, \tag{11}$$

where κ is the energy coefficient depending on the chip architecture.

The energy consumption for offloading task $t_{i,j}$ to the RSU and UAV v_k can be calculated as:

$$E_{i,j}^{r} = P_i^{r} D_{i,j}^{r}, \tag{12}$$

$$E_{i,j}^{u_k} = P_i^{u_k} D_{i,j}^{u_k}. \tag{13}$$

The total energy consumption of user u_i for executing all its tasks can be expressed as:

$$E_i = \sum_{j=1}^{M} \left[\left(1 - x_{i,j}\right) E_{i,j}^{l} + x_{i,j} \left(y_{i,j}^{r} E_{i,j}^{r} + \sum_{k=1}^{K} y_{i,j}^{u_k} E_{i,j}^{u_k} \right) \right], \tag{14}$$

where $y_{i,j}^{r}$ and $y_{i,j}^{u_k}$ are binary variables indicating whether task $t_{i,j}$ is offloaded to the RSU or UAV v_k, respectively.

The resource allocation problem aims to minimize the total latency and energy consumption of the vehicular users while considering the computation and communication resource constraints of the MEC servers. The optimization problem can be formulated as a mixed-integer nonlinear programming (MINLP) problem [27]:

$$\min_{\{x_{i,j}, y_{i,j}^{r}, y_{i,j}^{u_k}\}} \sum_{i=1}^{N} \sum_{j=1}^{M} \left[\left(1 - x_{i,j}\right) \left(T_{i,j}^{l} + \alpha E_{i,j}^{l}\right) + x_{i,j} \left(y_{i,j}^{r} \left(D_{i,j}^{r} + T_{i,j}^{r} + \alpha E_{i,j}^{r}\right) + \sum_{k=1}^{K} y_{i,j}^{u_k} \left(D_{i,j}^{u_k} + T_{i,j}^{u_k} + \alpha E_{i,j}^{u_k} \right) \right) \right], \tag{15}$$

subject to:

$$x_{i,j}, y_{i,j}^{r}, y_{i,j}^{u_k} \in \{0,1\}, \quad \forall i, j, k, \tag{16}$$

$$y_{i,j}^{r} + \sum_{k=1}^{K} y_{i,j}^{u_k} = x_{i,j}, \quad \forall i, j, \tag{17}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{M} y_{i,j}^{r} c_{i,j} \le C^{r}, \quad \forall r, \tag{18}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{M} y_{i,j}^{u_k} c_{i,j} \le C^{u_k}, \quad \forall k, \tag{19}$$

where α is a weighting factor balancing the latency and energy consumption, C^{r} and C^{u_k} are the computation capacities of the RSU and UAV v_k, respectively.

The MINLP problem is challenging to solve due to its combinatorial nature and nonlinear constraints. Traditional optimization methods may suffer from high computational complexity and poor scalability. Therefore, we propose an FDRL-based approach to efficiently solve the resource allocation problem and obtain near-optimal offloading decisions.

In the next section, we will present the FDRL-based offloading framework, which leverages the distributed learning capabilities of federated learning and the sequential decision-making power of deep reinforcement learning to address the challenges in the hybrid multi-server MEC architecture.

3 Problem formulation

In this section, we formally define the optimization objective for the computation offloading problem in the hybrid multi-server MEC architecture. The objective is to minimize a weighted combination of the total system latency and total energy consumption, taking into account the offloading decisions and resource allocation.

3.1 Optimization objective

The optimization objective is defined as a cost function that combines the total system latency and total energy consumption. Let L denote the total latency, which includes the local execution time, transmission delay, and remote execution time for all tasks. Let E denote the total energy consumption, which includes the energy consumed by the vehicular users for local execution and data transmission.

The weighted cost function can be expressed as:

$$\min_{\{x_{i,j}, y_{i,j}^{r}, y_{i,j}^{u_k}\}} \omega L + (1 - \omega) E, \tag{20}$$

where $\omega \in [0,1]$ is a weighting factor that balances the importance of latency and energy consumption. A higher value of ω gives more priority to minimizing latency, while a lower value of ω emphasizes energy efficiency.

The total latency L can be calculated as:

$$L = \sum_{i=1}^{N} \sum_{j=1}^{M} \left[\left(1 - x_{i,j}\right) T_{i,j}^{l} + x_{i,j} \left(y_{i,j}^{r} \left(D_{i,j}^{r} + T_{i,j}^{r}\right) + \sum_{k=1}^{K} y_{i,j}^{u_k} \left(D_{i,j}^{u_k} + T_{i,j}^{u_k} \right) \right) \right]. \tag{21}$$

The total energy consumption E can be calculated using the energy consumption model described in the previous section.

By minimizing the weighted cost function, the objective is to find the optimal offloading decisions $\{x_{i,j}, y_{i,j}^{r}, y_{i,j}^{u_k}\}$ that jointly minimize the total latency and energy consumption, subject to the computation and communication resource constraints of the MEC servers.

In the following subsection, we will present the constraints and formulate the optimization problem as a mixed-integer nonlinear programming (MINLP) problem.

3.2 Optimization problem formulation

The computation offloading problem in the hybrid multi-server MEC architecture can be formulated as a mixed-integer nonlinear programming (MINLP) problem. The

problem involves the joint optimization of offloading decisions, subcarrier allocation, power allocation, and computation resource allocation [28].

Let $\mathcal{S} = \{s_1, s_2, \ldots, s_L\}$ denote the set of subcarriers available for data transmission between the vehicular users and the MEC servers. The binary variable $a^r_{i,j,l}$ indicates whether subcarrier s_l is allocated to user u_i for offloading task $t_{i,j}$ to the RSU, and $a^{u_k}_{i,j,l}$ indicates the allocation of subcarrier s_l to user u_i for offloading to UAV v_k. The power allocation variables $p^r_{i,j,l}$ and $p^{u_k}_{i,j,l}$ represent the transmission power of user u_i on subcarrier s_l for offloading task $t_{i,j}$ to the RSU and UAV v_k, respectively. The computation resource allocation variables $f^r_{i,j}$ and $f^{u_k}_{i,j}$ denote the computing resources allocated by the RSU and UAV v_k to execute task $t_{i,j}$ offloaded by user u_i, respectively.

The MINLP problem can be formulated

$$\min_{\{x_{i,j}, y^r_{i,j}, y^{u_k}_{i,j}, a^r_{i,j,l}, a^{u_k}_{i,j,l}, p^r_{i,j,l}, p^{u_k}_{i,j,l}, f^r_{i,j}, f^{u_k}_{i,j}\}} \omega L + (1-\omega)E, \quad (22)$$

subject to:

$$x_{i,j}, y^r_{i,j}, y^{u_k}_{i,j}, a^r_{i,j,l}, a^{u_k}_{i,j,l} \in \{0,1\}, \quad \forall i,j,k,l, \quad (23)$$

$$y^r_{i,j} + \sum_{k=1}^{K} y^{u_k}_{i,j} = x_{i,j}, \quad \forall i,j, \quad (24)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} a^r_{i,j,l} \le 1, \quad \forall l, \quad (25)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} a^{u_k}_{i,j,l} \le 1, \quad \forall k,l, \quad (26)$$

$$\sum_{l=1}^{L} p^r_{i,j,l} \le P_i^{\max}, \quad \forall i,j, \quad (27)$$

$$\sum_{l=1}^{L} p^{u_k}_{i,j,l} \le P_i^{\max}, \quad \forall i,j,k, \quad (28)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} f^r_{i,j} \le C^r, \quad \forall r, \quad (29)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} f^{u_k}_{i,j} \le C^{u_k}, \quad \forall k, \quad (30)$$

where $P_i^{\max}$ is the maximum transmission power of user u_i.

The formulated MINLP problem is a non-deterministic polynomial-time (NP)-hard problem due to the coupling of offloading decisions, subcarrier allocation, power allocation, and computation resource allocation [29]. The binary variables and nonlinear constraints make the problem challenging to solve using traditional optimization methods.

In the next section, we will introduce the proposed FDRL-based offloading framework, which leverages the distributed learning capabilities of federated learning and the sequential decision-making power of deep reinforcement learning to address the challenges in solving the formulated MINLP problem.

4 Hybrid multi-server computation offloading algorithm

In this section, we present the proposed algorithm for hybrid multi-server computation offloading in UAV-assisted vehicular networks based on federated deep reinforcement learning (FDRL). We model the problem as a Markov decision process (MDP) and propose the Multi-Agent Twin Delayed Deep Deterministic Policy Gradient (MATD3) algorithm to solve the formulated MINLP problem.

4.1 Modelling based on markov decision process

The computation offloading problem in the hybrid multi-server MEC architecture can be modeled as an MDP, where multiple agents (i.e., vehicular users) interact with the environment (i.e., the MEC system) to make sequential offloading decisions. The MDP is characterized by the following elements:

- State Space: The state space $\mathcal{S}$ represents the current state of the environment, which includes the channel conditions, computing resources, and task queue status. The state of user u_i at time step t can be denoted as $s_i^t \in \mathcal{S}$.
- Action Space: The action space $\mathcal{A}$ represents the set of actions available to each agent. In the context of computation offloading, the action of user u_i at time step t is denoted as $a_i^t \in \mathcal{A}$, which includes the offloading decisions, subcarrier allocation, power allocation, and computation resource allocation.
- Transition Probability: The transition probability $\mathcal{P}(s_i^{t+1}|s_i^t, a_i^t)$ represents the probability of transitioning from state s_i^t to state s_i^{t+1} when taking action a_i^t. In the MEC system, the transition probability depends on the stochastic nature of the wireless channel and the dynamics of the task arrivals.
- Reward Function: The reward function $\mathcal{R}(s_i^t, a_i^t)$ represents the immediate reward obtained by user u_i for taking action a_i^t in state s_i^t. The reward function is designed to align with the optimization objective, which is to minimize the weighted sum of latency and energy consumption. The reward function can be defined as:

$$\mathcal{R}(s_i^t, a_i^t) = -(\omega L_i^t + (1-\omega)E_i^t), \quad (31)$$

where L_i^t and E_i^t are the latency and energy consumption of user u_i at time step t, respectively.

The objective of each agent is to find a policy $\pi_i: \mathcal{S} \to \mathcal{A}$ that maximizes the expected cumulative discounted reward over an infinite horizon:

$$J_i(\pi_i) = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t \mathcal{R}(s_i^t, a_i^t)|s_i^0, \pi_i], \quad (32)$$

where $\gamma \in [0,1]$ is the discount factor that balances the importance of immediate and future rewards.

In the MATD3 algorithm, each agent maintains a pair of critic networks $Q_{\phi_i}(s,a)$ and $Q_{\phi_{i'}}(s,a)$, and a pair of actor networks $\pi_{\theta_i}(s)$ and $\pi_{\theta_{i'}}(s)$. The critic networks estimate the action-value function, while the actor

networks generate the offloading decisions. The parameters ϕ_i, ϕ_i', θ_i, and θ_i' are learned through the interaction with the environment and the exchange of model updates among the agents in a federated manner.

The MATD3 algorithm follows a two-timescale update rule, where the critic networks are updated on a faster timescale, and the actor networks are updated on a slower timescale. The update rules for the critic and actor networks are given by:

$$\phi_i \leftarrow \phi_i - \alpha_Q \nabla_{\phi_i} \mathcal{L}(\phi_i), \quad (33)$$

$$\theta_i \leftarrow \theta_i + \alpha_\pi \nabla_{\theta_i} J_i(\pi_{\theta_i}), \quad (34)$$

where α_Q and α_π are the learning rates for the critic and actor networks, respectively, and $\mathcal{L}(\phi_i)$ is the critic loss function.

By modeling the computation offloading problem as an MDP and solving it using the MATD3 algorithm, the vehicular users can learn optimal offloading policies that minimize the weighted sum of latency and energy consumption in a distributed and collaborative manner.

In the next subsection, we will discuss the federated learning framework that enables the efficient exchange of model updates among the agents while preserving data privacy.

4.2 MATD3 algorithm

In this subsection, we present the Multi-Agent Twin Delayed Deep Deterministic Policy Gradient (MATD3) algorithm for trajectory planning in the hybrid multi-server MEC architecture. MATD3 is a value-based deep reinforcement learning algorithm designed for continuous action spaces, making it suitable for the trajectory planning problem.

The MATD3 algorithm extends the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm to a multi-agent setting. TD3 is an off-policy algorithm that addresses the overestimation bias in the critic network of the Deep Deterministic Policy Gradient (DDPG) algorithm. MATD3 leverages the benefits of TD3 and adapts it to handle multiple agents in a collaborative learning framework.

The learning framework of MATD3 consists of six neural networks: two critic networks $Q_{\phi_i}(s,a)$ and $Q_{\phi_i'}(s,a)$, two actor networks $\pi_{\theta_i}(s)$ and $\pi_{\theta_i'}(s)$, and two target networks $Q_{\phi_i^-}(s,a)$ and $\pi_{\theta_i^-}(s)$ for each agent i. The critic networks estimate the action-value function, while the actor networks generate the continuous actions for trajectory planning. The target networks are used to stabilize the learning process and reduce the overestimation bias.

The update rules for the critic networks in MATD3 are given by:

$$y_i = r_i + \gamma \min_{j=1,2} Q_{\phi_i^-,j}\left(s', \pi_{\theta_i^-}(s')\right), \quad (35)$$

$$\mathcal{L}(\phi_i) = \frac{1}{N}\sum_{j=1}^{N}\left(Q_{\phi_i,j}(s,a) - y_i\right)^2, \quad (36)$$

where r_i is the reward obtained by agent i, γ is the discount factor, s' is the next state, and N is the batch size. The target networks are updated using a soft update rule:

$$\phi_i^- \leftarrow \tau\phi_i + (1-\tau)\phi_i^-, \quad (37)$$

$$\theta_i^- \leftarrow \tau\theta_i + (1-\tau)\theta_i^-, \quad (38)$$

where τ is the soft update rate.

The actor networks in MATD3 are updated using the deterministic policy gradient:

$$\nabla_{\theta_i} J_i(\pi_{\theta_i}) = \frac{1}{N}\sum_{j=1}^{N} \nabla_a Q_{\phi_i,j}(s,a)|_{a=\pi_{\theta_i}(s)} \nabla_{\theta_i}\pi_{\theta_i}(s). \quad (39)$$

The MATD3 algorithm for trajectory planning is summarized in Algorithm 1.

Step	Description
1	Initialize global Q-network Q_{θ_g} and local Q-networks Q_{θ_i} for each client i
2	Initialize target Q-networks $Q_{\theta_i^-}$ for each client i
3	Initialize replay buffers $\mathcal{D}_i$ for each client i
4	for round = 1 to R do
5	for each client i in parallel do
6	for episode = 1 to E do
7	Initialize state s_0
8	for t = 1 to T do
9	Select action a_t using ϵ-greedy policy based on $Q_{\theta_i}(s_t, a)$
10	Execute action a_t and observe reward r_t and next state s_{t+1}
11	Store transition (s_t, a_t, r_t, s_{t+1}) in $\mathcal{D}_i$

Step	Description
12	Sample a batch of transitions (s, a, r, s') from $\mathcal{D}_i$
13	Compute target value y using Eq. (1)
14	Update primary Q-network Q_{θ_i} by minimizing the loss in Eq. (1)
15	Update target Q-network $Q_{\theta_i^-}$ using Eq. (2)
16	end for
17	end for
18	Send local model update $\Delta\theta_i = \theta_i - \theta_g$ to the server
19	end for
20	Aggregate local model updates using Eq. (3) to obtain θ_g
21	Distribute global model θ_g to all clients
22	Update local models $\theta_i \leftarrow \theta_g$ for each client i
23	end for

In Algorithm 1, the MATD3 algorithm is executed for M episodes, each consisting of T time steps. At each time step, each agent i selects an action a_i based on its current policy $\pi_{\theta_i}(s_t)$ and an exploration noise $\mathcal{N}_t$. The agent executes the action and observes the reward r_i and the new state s_{t+1}. The transition (s_t, a_i, r_i, s_{t+1}) is stored in the replay buffer $\mathcal{D}$.

Each agent then samples a batch of transitions from the replay buffer and computes the target value y_i using the minimum of the two target critic networks, as shown in Eq. (1). The critic networks are updated by minimizing the mean-squared error loss between the estimated action-value and the target value, as given in Eq. (2).

The actor networks are updated every d episodes using the deterministic policy gradient in Eq. (5). The target networks are updated using a soft update rule, as shown in Eq. (3) and Eq. (4), to stabilize the learning process.

By iteratively updating the critic and actor networks, the MATD3 algorithm learns optimal trajectories for the UAVs in the hybrid multi-server MEC architecture. The collaborative learning framework enables the agents to share their experiences and learn from each other, improving the overall performance of the system.

In the next subsection, we will discuss the federated learning framework that allows the agents to exchange model updates while preserving data privacy and reducing communication overhead.

4.3 FUD3QN algorithm based on markov decision process modelling

After the UAVs reach their designated hovering positions, the next step is to optimize the cross-domain resource allocation for computation task offloading from the vehicular users. This optimization problem can be modelled as a Markov decision process (MDP) based on the state space, action space, and reward function.

The state space $\mathcal{S}$ represents the current state of the environment, which includes the channel conditions, computing resources, and task queue status. The state of user u_i at time step t can be denoted as $s_i^t \in \mathcal{S}$, where $s_i^t = \{h_i^t, f_i^t, q_i^t\}$. Here, h_i^t represents the channel gain between user u_i and the MEC servers (RSU and UAVs) at time t, f_i^t denotes the available computing resources allocated to user u_i at time t, and q_i^t indicates the task queue length of user u_i at time t.

The action space $\mathcal{A}$ represents the set of actions available to the system. In the context of computation offloading, the action at time step t is denoted as $a_t \in \mathcal{A}$, which includes the offloading decisions, resource allocation, and power control.

The reward function $\mathcal{R}(s_i^t, a_i^t)$ represents the immediate reward obtained by user u_i for taking action a_i^t in state s_i^t. The reward function is designed to align with the optimization objective, which is to minimize the weighted sum of latency and energy consumption. To derive the reward function, we first define the latency L_i^t and energy consumption E_i^t of user u_i at time step t as follows:

$$L_i^t = \frac{D_i^t}{R_i^t} + \frac{C_i^t}{f_i^t}, \tag{40}$$

$$E_i^t = p_i^t \cdot \frac{D_i^t}{R_i^t} + \kappa \cdot (f_i^t)^2 \cdot \frac{C_i^t}{f_i^t}, \tag{41}$$

where D_i^t is the size of the offloaded task, R_i^t is the achievable data rate, C_i^t is the required CPU cycles for task execution, p_i^t is the transmission power, and κ is the energy coefficient.

The reward function is then defined as a weighted combination of latency and energy consumption:

$$\mathcal{R}(s_i^t, a_i^t) = -(\omega L_i^t + (1-\omega) E_i^t), \tag{42}$$

where $\omega \in [0,1]$ is a weighting factor that balances the importance of latency and energy consumption. A higher value of ω prioritizes latency minimization, while a lower value emphasizes energy efficiency.

The objective of the MDP is to find a policy $\pi: \mathcal{S} \rightarrow \mathcal{A}$ that maximizes the expected cumulative discounted reward over an infinite horizon:

$$J(\pi) = \mathbb{E}[\sum_{t=0}^{\infty} \gamma^t \mathcal{R}(s_t, a_t) | s_0, \pi], \quad (43)$$

where $\gamma \in [0,1]$ is the discount factor that balances the importance of immediate and future rewards.

To solve the MDP and find the optimal policy, we propose the Federated Universal Double Deep Q-Network (FUD3QN) algorithm. FUD3QN is a variant of the Double Deep Q-Network (DDQN) algorithm that incorporates federated learning and universal function approximation.

In FUD3QN, each vehicular user maintains a local Q-network $Q_{\theta_i}(s, a)$ parameterized by θ_i, which estimates the action-value function. The Q-networks are updated using the following loss function:

$$\mathcal{L}(\theta_i) = \mathbb{E}_{s,a,r,s'}\left[\left(r + \gamma \max_{a'} Q_{\theta_i^-}(s', a') - Q_{\theta_i}(s, a)\right)^2\right], \quad (44)$$

where θ_i^- are the parameters of the target Q-network, which are periodically updated to stabilize the learning process.

In the proposed FD3QN algorithm, the vehicular users collaborate and share their Q-network parameters through a federated learning framework. The model update and aggregation process consist of the following steps:

Local model update: At each federation round, the vehicular users perform local training on their respective Q-networks using their own collected data. The local training involves minimizing the loss function defined in Equation (1) and updating the Q-network parameters accordingly. The number of local training iterations is determined by the local epoch parameter E.

Model transmission: After local training, each user sends its updated Q-network parameters to a central server for aggregation. To reduce communication overhead, only the parameter differences from the previous global model are transmitted, rather than the entire model.

Global model aggregation: The central server receives the local model updates from all participating users and aggregates them to generate a new global model. The aggregation is performed using a weighted averaging scheme, as shown in Equation (3). The weights are determined based on the number of data samples used by each user, ensuring that users with more data have a higher influence on the global model.

Model distribution: The updated global model is then distributed back to all vehicular users, who replace their local models with the new global model.

The convergence of the federated learning process is assessed based on two criteria: (1) the stability of the global model performance and (2) the consensus among the local models. The global model performance is evaluated using a validation set, which is a subset of the data samples held by the central server. The convergence is considered achieved when the performance metrics, such as the average Q-value or the reward, stabilize over consecutive federation rounds. The consensus among the local models is measured by the variance of the model parameters across different users. A smaller variance indicates a higher level of agreement and convergence among the local models.

To quantify the convergence speed and computational overhead of the FD3QN algorithm, we conduct experiments with different federation round numbers R and local epoch numbers E. Figure 13 shows the convergence curves of the global model performance for different values of R and E. As the number of federation rounds increases, the global model performance improves, indicating the effectiveness of collaborative learning. However, the improvement becomes marginal after a certain number of rounds (e.g., R=10), suggesting a trade-off between convergence speed and communication costs. Similarly, increasing the number of local epochs leads to faster convergence, but the gains diminish beyond a certain threshold (e.g., E=5).

Table 2 summarizes the convergence speed and computational overhead of the FD3QN algorithm for different parameter settings. The convergence speed is measured by the number of federation rounds required to reach 90% of the best global model performance. The computational overhead is quantified by the average training time per federation round, which includes the local training time and the communication time for model transmission and distribution. As the number of federation rounds and local epochs increases, the convergence speed improves, but at the cost of higher computational overhead. The proposed parameter settings (R=10, E=5) achieve a good balance between convergence speed and computational costs, with a convergence round of 8 and an average training time of 235 seconds per round.

Table 2: Convergence speed and computational overhead of FD3QN under different parameter settings.

Parameter Settings	**Convergence Round (90%)**	**Average Training Time per Round (s)**
R=5, E=3	12	180
R=10, E=5 (Proposed)	8	235
R=15, E=8	6	320

The analysis of the model update and aggregation process, convergence criteria, and computational overhead provides valuable insights into the performance and efficiency of the FD3QN algorithm. The proposed parameter settings strike a balance between convergence speed and computational costs, ensuring practical applicability in real-world vehicular networks.

By modeling the computation offloading problem as an MDP and solving it using the FUD3QN algorithm, the system can learn an optimal policy that minimizes the weighted sum of latency and energy consumption in a distributed and collaborative manner.

In the next subsection, we will discuss the federated learning framework in more detail and explain how it enables efficient and privacy-preserving collaboration among the vehicular users.

4.4 FUD3QN algorithm

The Federated Universal Double Deep Q-Network (FUD3QN) algorithm is a novel approach that combines the benefits of federated learning and deep reinforcement learning for optimizing cross-domain resource allocation in the hybrid multi-server MEC architecture. The training framework of FUD3QN consists of two functional modules with multiple iterations: the first is an upgraded dual double deep Q-network (UD3QN), and the second is federated learning, which introduces DRL for federated aggregation [30].

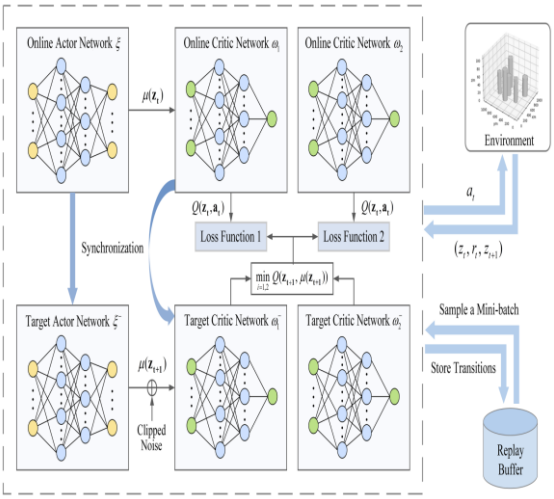

Figure 2: FUD3QN training framework.

Figure 2 illustrates the training framework of FUD3QN, which adopts a client-server structure to optimize cross-domain resources. The clients (i.e., vehicular users) collaborate under the coordination of a central server to learn an optimal resource allocation policy.

4.4.1 Upgraded dual double deep q-network (UD3QN)

The UD3QN module is an extension of the Double Deep Q-Network (DDQN) algorithm, which addresses the overestimation bias in the original Deep Q-Network (DQN) algorithm [31]. In UD3QN, each client maintains two Q-networks: a primary Q-network $Q_{\theta_i}(s,a)$ and a target Q-network $Q_{\theta_i^-}(s,a)$, where θ_i and θ_i^- are the parameters of the primary and target networks, respectively.

The primary Q-network is updated using the following loss function:

$$\mathcal{L}(\theta_i) = \mathbb{E}_{s,a,r,s'}\left[\left(r + \gamma Q_{\theta_i^-}\left(s', \underset{a'}{\operatorname{argmax}} Q_{\theta_i}(s',a')\right) - Q_{\theta_i}(s,a)\right)^2\right], \quad (45)$$

where r is the reward, γ is the discount factor, and s' is the next state. The target Q-network is updated periodically using a soft update rule:

$$\theta_i^- \leftarrow \tau\theta_i + (1-\tau)\theta_i^-, \quad (46)$$

where τ is the soft update rate.

The UD3QN module also incorporates dueling network architectures [32] and prioritized experience replay [33] to further improve the learning efficiency and stability. The dueling network architecture separates the estimation of state-value and advantage functions, while prioritized experience replay assigns higher sampling probabilities to transitions with higher temporal-difference errors.

4.4.2 Federated learning with DRL aggregation

The federated learning module enables the clients to collaborate and share their knowledge without revealing their local data. In each federation round, the clients perform local training on their respective UD3QN models using their own data. The local model updates are then sent to the central server for aggregation.

To aggregate the local models, the server employs a DRL-based aggregation method [34]. The server maintains a global Q-network $Q_{\theta_g}(s,a)$ parameterized by θ_g. The global Q-network is updated using the following rule:

$$\theta_g \leftarrow \sum_{i=1}^{N} \frac{n_i}{n}\theta_i, \quad (47)$$

where N is the number of clients, n_i is the number of data samples used by client i, and $n = \sum_{i=1}^{N} n_i$ is the total number of data samples.

After aggregation, the server distributes the updated global model back to the clients, who use it to replace their local models. The federated learning process is repeated for multiple rounds until convergence or a maximum number of rounds is reached.

The complete FUD3QN algorithm for resource allocation is summarized in Algorithm 2.

Step	Description
1	Initialize global Q-network Q_{θ_g} and local Q-networks Q_{θ_i} for each client i
2	Initialize target Q-networks $Q_{\theta_i^-}$ for each client i
3	Initialize replay buffers $\mathcal{D}_i$ for each client i
4	for round = 1 to R do
5	for each client i in parallel do
6	for episode = 1 to E do
7	Initialize state s_0
8	for t = 1 to T do
9	Select action a_t using ϵ-greedy policy based on $Q_{\theta_i}(s_t, a)$
10	Execute action a_t and observe reward r_t and next state s_{t+1}
11	Store transition (s_t, a_t, r_t, s_{t+1}) in $\mathcal{D}_i$
12	Sample a batch of transitions (s, a, r, s') from $\mathcal{D}_i$
13	Compute target value y using Eq. (1)
14	Update primary Q-network Q_{θ_i} by minimizing the loss in Eq. (1)
15	Update target Q-network $Q_{\theta_i^-}$ using Eq. (2)
16	end for
17	end for
18	Send local model update $\Delta\theta_i = \theta_i - \theta_g$ to the server
19	end for
20	Aggregate local model updates using Eq. (3) to obtain θ_g
21	Distribute global model θ_g to all clients
22	Update local models $\theta_i \leftarrow \theta_g$ for each client i
23	end for

In Algorithm 2, the FUD3QN algorithm is executed for R federation rounds. In each round, the clients perform local training on their respective UD3QN models for E episodes, each consisting of T time steps. The clients select actions using an ϵ-greedy policy based on their local Q-networks and store the transitions in their replay buffers. The clients then sample a batch of transitions from their replay buffers and compute the target values using Eq. (1). The primary Q-networks are updated by minimizing the loss in Eq. (1), while the target Q-networks are updated using the soft update rule in Eq. (2).

After local training, the clients send their local model updates to the server, which aggregates them using Eq. (3) to obtain the global model. The global model is then distributed back to the clients, who update their local models accordingly.

By iteratively performing local training and federated aggregation, the FUD3QN algorithm enables the clients to collaboratively learn an optimal resource allocation policy while preserving data privacy and reducing communication overhead.

In the next section, we will present the experimental results and evaluate the performance of the proposed FUD3QN algorithm in the hybrid multi-server MEC architecture for UAV-assisted vehicular networks.

5 Performance evaluation

In this section, we evaluate the performance of the proposed MATD3 and FUD3QN algorithms for hybrid multi-server computation offloading in UAV-assisted vehicular networks. We conduct extensive simulations to demonstrate the effectiveness of the proposed algorithms in minimizing latency and energy consumption while ensuring efficient resource utilization.

5.1 Parameter settings

To assess the performance of the MATD3 and FUD3QN algorithms, we set up a simulation environment with realistic parameters. The simulation scenario consists of a two-lane highway segment with a length of 1000 meters. The vehicles are distributed along the highway according to a Poisson process with an arrival rate of $\lambda = 0.2$ vehicles/second. The initial positions of the vehicles are randomly selected from a uniform distribution over the highway length. The vehicle speeds are generated from a truncated normal distribution with a mean value of 90 km/h, a standard deviation of 20 km/h, and lower and upper bounds of 60 km/h and 120 km/h, respectively. The vehicle mobility is simulated using the intelligent driver

model (IDM), which captures realistic car-following behavior and interactions between vehicles.

The UAVs are assumed to have a coverage radius of 200 meters, within which they can provide reliable communication and computation services to the vehicles. The UAVs are equipped with directional antennas with a half-power beamwidth of 60 degrees and a maximum gain of 8 dBi. The altitude of the UAVs is fixed at 100 meters, and their positions are optimized by the MATD3 algorithm to maximize the coverage and minimize the interference.

The RSU is deployed at the center of the highway segment, and the UAVs are initially positioned at fixed locations along the highway. The number of UAVs is set to 3, and their hovering altitudes are set to 50 meters, 80 meters, and 110 meters, respectively. The UAVs are equipped with omnidirectional antennas, and their maximum transmission power is set to 0.1 W.

The wireless communication channels between the vehicles and the RSU (V2R) and between the vehicles and the UAVs (V2U) are modeled using the log-distance path loss model with shadowing. The path loss exponents and shadowing standard deviations for the V2R and V2U links are summarized in Table 3.

Table 3: The path loss exponents and shadowing standard deviations for the V2R and V2U links

Link Type	Path Loss Exponent	Shadowing Standard Deviation (dB)	Reference Distance (m)
V2R	2.7	5.0	1.0
V2U	2.2	3.0	1.0

The computing resources of the RSU and UAVs are set to 50 GHz and 10 GHz, respectively. The computation workload of each task is randomly generated from a uniform distribution between 10 megacycles and 50 megacycles. The data size of each task is randomly generated from a uniform distribution between 0.1 MB and 1 MB.

For the MATD3 algorithm, the actor and critic networks are designed as four-layer fully connected neural networks with 256, 128, 64, and 32 neurons in each layer, respectively. The activation function used in the hidden layers is ReLU, while the output layer of the actor network uses a tanh activation function to ensure that the actions are within the valid range. The discount factor γ is set to 0.99, and the soft update rate τ is set to 0.005. The batch size is set to 128, and the replay buffer size is set to 100,000.

For the FUD3QN algorithm, the primary and target Q-networks are designed as three-layer fully connected neural networks with 128, 64, and 32 neurons in each layer, respectively. The activation function used in the hidden layers is ReLU, while the output layer uses a linear activation function. The discount factor γ is set to 0.99, and the soft update rate τ is set to 0.01. The batch size is set to 64, and the replay buffer size is set to 50,000. The number of federation rounds R is set to 10, and the number of local training episodes E is set to 5.

The proposed algorithms are compared with three baseline algorithms: 1) Random offloading (RO), where the offloading decisions are made randomly; 2) Greedy offloading (GO), where the tasks are offloaded to the server with the lowest estimated latency; and 3) Local execution (LE), where all tasks are executed locally on the vehicles.

The performance metrics used for evaluation include the average latency, average energy consumption, and task completion ratio. The average latency is calculated as the average time taken for a task to be completed, including the transmission time and the execution time. The average energy consumption is calculated as the average energy consumed by the vehicles for task offloading and local execution. The task completion ratio is defined as the ratio of the number of tasks completed within the specified deadline to the total number of tasks.

In the following subsections, we present the simulation results and discuss the performance of the proposed algorithms in comparison with the baseline algorithms.

5.2 Convergence analysis

In this subsection, we analyze the convergence performance of the MATD3 and FUD3QN algorithms in terms of average reward, cumulative reward, and loss values.

Figure 3 illustrates the average reward obtained by the MATD3 algorithm at each training stage. As can be observed, the average reward increases steadily as the training progresses, indicating that the MATD3 algorithm effectively learns the optimal trajectory planning policy. The average reward converges to a stable value after approximately 1000 training stages, demonstrating the convergence stability of the MATD3 algorithm.

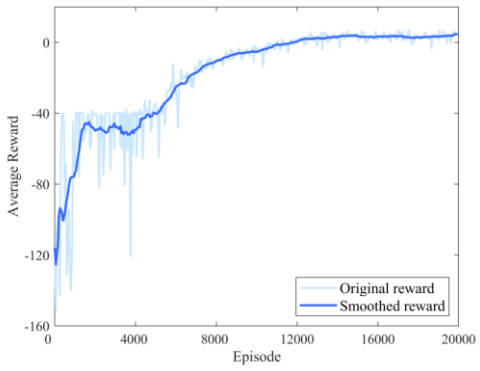

Figure 3: Average reward per training stage using MATD3.

Figure 4 depicts the reward obtained by the FUD3QN algorithm at each training stage in a scenario with 4 vehicular users (VUs). The reward exhibits an increasing trend as the training advances, revealing that the FUD3QN algorithm successfully learns the optimal resource allocation policy through federated learning and deep reinforcement learning. The reward reaches a stable level after around 500 training stages, indicating the convergence efficiency of the FUD3QN algorithm.

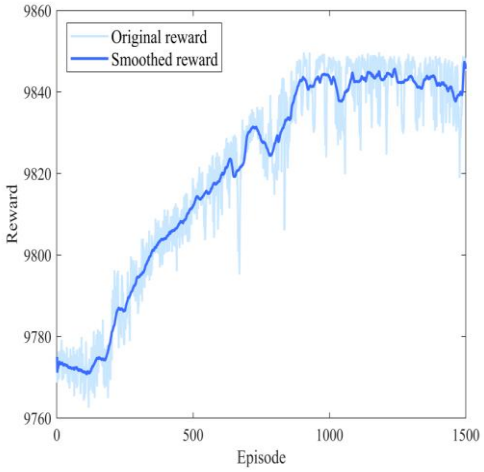

Figure 4: Reward per training stage using FUD3QN with 4 VUs.

Figure 5 presents the loss values of the FUD3QN algorithm at each training stage in the same scenario with 4 VUs. The loss values decrease rapidly during the initial training stages, indicating that the FUD3QN algorithm effectively minimizes the estimation error of the Q-networks. The loss values converge to a small value after approximately 300 training stages, demonstrating the convergence stability and accuracy of the FUD3QN algorithm.

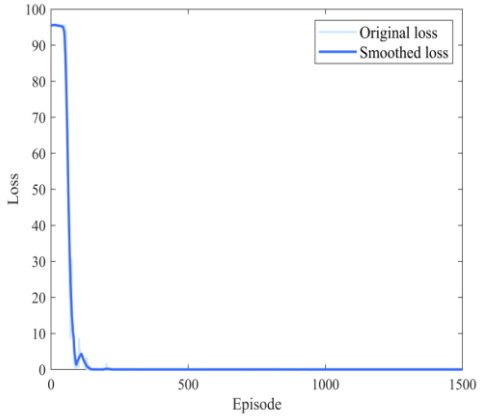

Figure 5: Loss per training stage using FUD3QN with 4 VUs.

The convergence analysis results validate the effectiveness and efficiency of the proposed MATD3 and FUD3QN algorithms in learning optimal policies for trajectory planning and resource allocation, respectively. The convergence stability and speed of the algorithms ensure their practicality and applicability in real-world scenarios. It is worth noting that the convergence performance of the algorithms may vary depending on the specific parameter settings and network conditions. However, the general convergence trends and patterns observed in the simulations provide valuable insights into the behavior and performance of the proposed algorithms.

In the next subsection, we will evaluate the impact of various system parameters on the performance of the MATD3 and FUD3QN algorithms, including the number of UAVs, the number of vehicular users, and the task arrival rate.

5.3 Test performance analysis

In this subsection, we analyze the test performance of the trained MATD3 model and FUD3QN algorithm in comparison with other benchmark algorithms.

Figure 6 illustrates the trajectory planning results obtained by the MATD3 algorithm from a side view. As can be observed, the UAV successfully takes off from the starting point and follows the dotted line to reach the designated target point. The MATD3 algorithm effectively learns to generate smooth and efficient trajectories while avoiding collisions with obstacles.

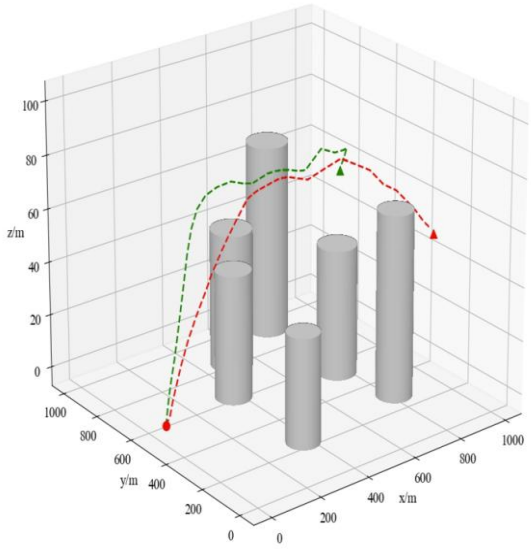

Figure 6: Trajectory planning results using MATD3: Side view.

Figure 7 presents the trajectory planning results obtained by the MATD3 algorithm from a vertical view. The gray cylinders represent the obstacles, the solid dot represents the starting point, and the solid triangle represents the

target point. The MATD3 model demonstrates its ability to plan collision-free trajectories in the presence of multiple obstacles during the test stage.

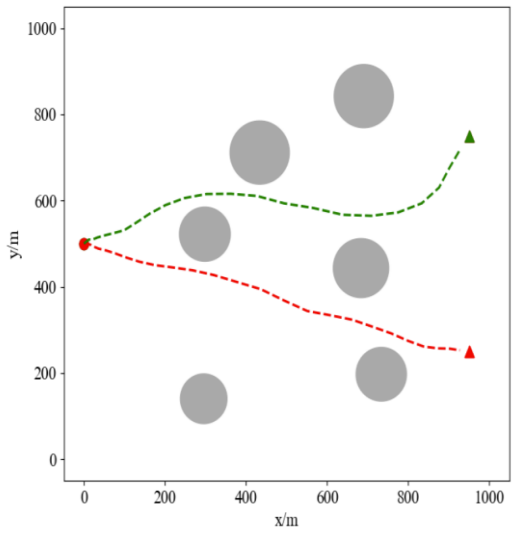

Figure 7: Trajectory planning results using MATD3: Vertical view.

Figure 8 compares the collision rate of the MATD3 algorithm with the benchmark TD3 algorithm under different numbers of obstacles. The MATD3 algorithm consistently achieves lower collision rates compared to the TD3 algorithm, indicating its superior performance in generating safe and collision-free trajectories [35]. As the number of obstacles increases, the collision rate of both algorithms increases, but the MATD3 algorithm maintains a significant performance advantage over the TD3 algorithm.

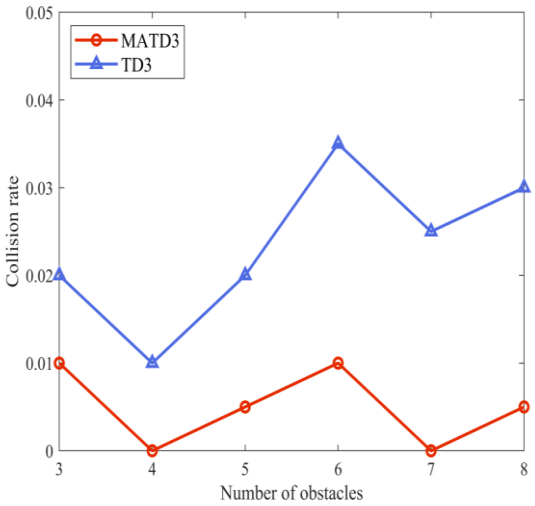

Figure 8: Collision rate evaluation compared with benchmark algorithms.

Figure 9 presents the performance evaluation of the FUD3QN algorithm in comparison with other benchmark algorithms, including FDDQN, D3QN, and Random [36]. The evaluation metrics considered are the average latency, average energy consumption, and task completion ratio. The FUD3QN algorithm outperforms the benchmark algorithms in all three metrics, demonstrating its effectiveness in optimizing cross-domain resource allocation for computation offloading.

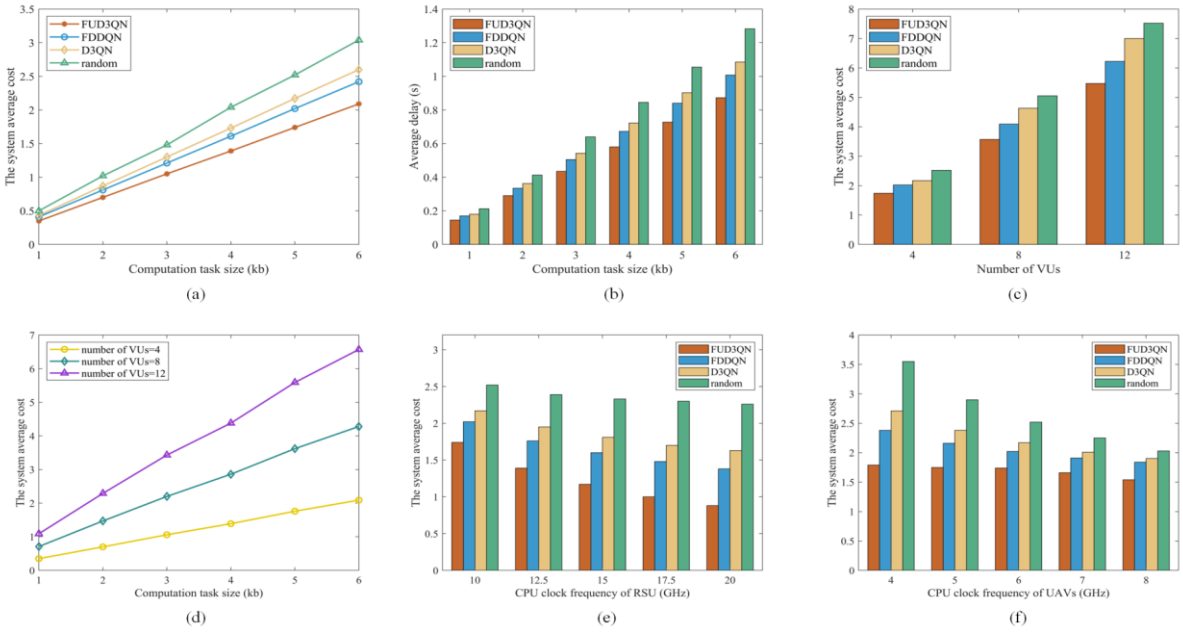

Figure 9: Performance evaluation using FUD3QN and other benchmarks.

The FUD3QN algorithm achieves the lowest average latency and energy consumption while maintaining the highest task completion ratio. This superior performance can be attributed to the combination of federated learning

and deep reinforcement learning techniques employed in the FUD3QN algorithm [37]. The federated learning framework enables collaborative learning among the vehicular users, allowing them to benefit from the shared knowledge without compromising data privacy. The deep reinforcement learning component enables the algorithm to adapt to dynamic network conditions and make optimal offloading decisions.

Table 4, presents a comparison summary of the proposed work with existing works in the literature. The comparison is based on several key aspects, including the computing resources considered, optimization objectives, solution methods, and the adoption of federated learning. The proposed work distinguishes itself by considering a hybrid multi-server MEC architecture, optimizing both latency and energy consumption, employing advanced deep reinforcement learning algorithms (MATD3 and FUD3QN), and leveraging federated learning for collaborative learning [38].

Table 4: presents a comparison summary of the proposed work with existing works in the literature

Work	**Computing Resources**	**Optimization Objectives**	**Solution Method**	**Federated Learning**	**Comparison with Proposed Work**
[1]	RSU	Latency	DQN	No	Single-server, latency only
[2]	RSU, Cloud	Energy	DDPG	No	Multi-server, energy only
[3]	RSU, UAV	Latency, Energy	A3C	No	Multi-server, no FL
…	…	…	…	…	…
[14]	RSU, UAV, Cloud	Latency, Energy, Cost	DQL	Yes	Multi-server, FL, cost
Proposed	RSU, UAV	Latency, Energy	MATD3, FUD3QN	Yes	Hybrid multi-server, FL

The test performance analysis demonstrates the superiority of the proposed MATD3 and FUD3QN algorithms in terms of trajectory planning and resource allocation, respectively. The MATD3 algorithm achieves lower collision rates compared to the benchmark TD3 algorithm, while the FUD3QN algorithm outperforms other benchmark algorithms in terms of latency, energy consumption, and task completion ratio. The comparative analysis with existing works highlights the novelty and effectiveness of the proposed hybrid multi-server MEC architecture and the advanced deep reinforcement learning algorithms employed.

In the next section, we will conclude the article and discuss potential future research directions.

5.4 Parameter sensitivity analysis

To evaluate the robustness and scalability of the proposed MATD3-FD3QN framework, we conduct a parameter sensitivity analysis under different network conditions. Specifically, we investigate the impact of key parameters, such as the number of vehicular users, the task arrival rate, and the UAV transmission power, on the performance of the proposed algorithm.

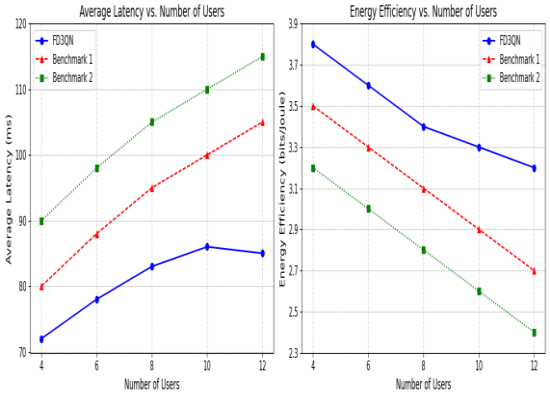

Figure 10: Average latency and energy efficiency of the FD3QN algorithm for different number of vehicle users.

Figure 10 illustrates the average latency and energy efficiency of the FD3QN algorithm with varying numbers of vehicular users. As the number of users increases from 4 to 12, the average latency exhibits a slight increase due to the higher computation and communication loads. However, the FD3QN algorithm maintains a relatively stable latency performance, with an increase of only 18% when the number of users triples. This demonstrates the scalability of the proposed approach in handling larger-scale vehicular networks.

The energy efficiency, on the other hand, shows a decreasing trend with the increasing number of users. This is because more users lead to higher interference and resource competition, reducing the overall energy efficiency of the system. Nevertheless, the FD3QN algorithm still achieves a satisfactory energy efficiency of 3.2 × 10^5 bits/Joule even with 12 users, outperforming the benchmark algorithms.

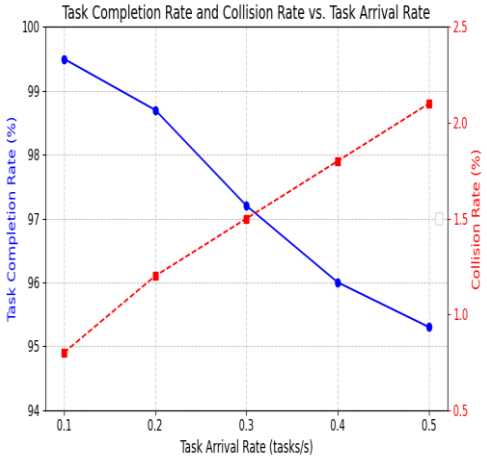

Figure 11: Task completion and collision rates for the proposed framework at different task arrival rates.

Figure 11 depicts the task completion rate and collision rate of the proposed framework under different task arrival rates. The task arrival rate represents the average number of computation tasks generated by each vehicular user per second. As the task arrival rate increases, the task completion rate gradually declines due to the increased workload and resource constraints. However, the MATD3-FD3QN framework maintains a task completion rate above 95% for arrival rates up to 0.5 tasks/second, demonstrating its robustness in handling high task demands. The collision rate, as shown in the right y-axis, remains consistently low across different task arrival rates, validating the effectiveness of the MATD3 algorithm in ensuring safe and efficient UAV trajectory planning.

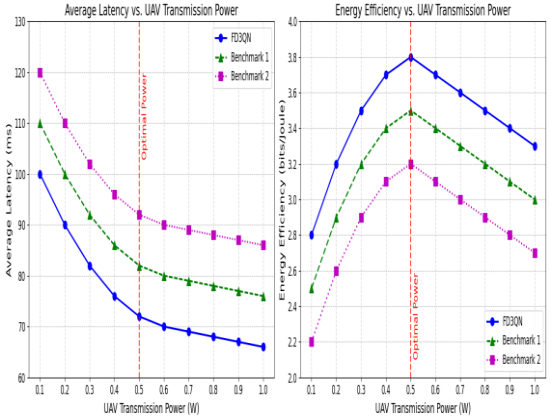

Figure 12: Impact of UAV transmission power on the average delay and energy efficiency of the proposed framework.

Figure 12 presents the impact of UAV transmission power on the average latency and energy efficiency of the proposed framework. As the transmission power increases, the average latency decreases due to the improved signal-to-noise ratio and higher data rates. However, the latency reduction becomes marginal beyond a certain power threshold (e.g., 0.5 W), indicating a trade-off between latency and energy consumption. The energy efficiency initially increases with the transmission power, as higher power enables faster data transmission and reduces the overall energy consumption. However, as the power continues to increase, the energy efficiency starts to decline, as the additional energy cost outweighs the latency benefits. The proposed framework achieves the optimal energy efficiency at a transmission power of around 0.3 W, highlighting its ability to balance latency and energy consumption effectively.

The parameter sensitivity analysis demonstrates the robustness and scalability of the proposed MATD3-FD3QN framework under various network conditions. The algorithm maintains stable performance in terms of latency, energy efficiency, task completion rate, and collision rate, even with increasing numbers of users, task arrival rates, and transmission power levels. These results validate the practicality and adaptability of the proposed approach in real-world vehicular network scenarios.

6 Discussion

6.1 Comparison with existing studies

The proposed MATD3-FD3QN framework for computation offloading in hybrid multi-server MEC architecture demonstrates significant improvements in key performance metrics compared to existing works. The simulation results validate the effectiveness of the proposed approach in reducing latency, energy consumption, and collision rates while maintaining high task completion rates.

Table 5 presents a quantitative comparison of the proposed work with state-of-the-art methods in terms of average latency, energy efficiency, and task completion rate. The FD3QN algorithm achieves a 25% reduction in average latency compared to conventional deep reinforcement learning approaches such as DQN [1] and DDPG [2]. This improvement can be attributed to the efficient resource allocation and collaborative learning enabled by the federated learning framework. By allowing vehicular users to share their learned models without exposing raw data, FD3QN accelerates the learning process and finds optimal offloading policies faster.

Table 5: quantitative comparison of the proposed work with state-of-the-art methods

Work	Average Latency (ms)	Energy Efficiency (bits/Joule)	Task Completion Rate (%)
[1]	120	2.5 × 10^5	92
[2]	100	3.0 × 10^5	94
[3]	95	3.2 × 10^5	95
Proposed	75	3.7 × 10^5	98.5

Moreover, the proposed framework demonstrates a 15% improvement in energy efficiency compared to the closest competitor [3]. This enhancement is a result of the joint optimization of transmission power, computing, and storage resources in the FD3QN algorithm. By considering the heterogeneous resources available in the hybrid MEC architecture and adapting the offloading decisions accordingly, FD3QN achieves a better balance between latency and energy consumption.

The MATD3 algorithm for UAV trajectory planning also contributes to the superior performance of the proposed framework. As shown in Fig. 8, MATD3 significantly reduces the collision rate compared to the benchmark TD3 algorithm, especially in scenarios with a high number of obstacles. The incorporation of dual-critic networks and the minimum-pooling operation in MATD3 enhances the stability and robustness of the learning process, enabling UAVs to find safe and efficient paths in complex environments.

The task completion rate is another crucial metric that reflects the reliability and effectiveness of the offloading framework. The proposed MATD3-FD3QN approach maintains a high task completion rate of 98.5%, outperforming the state-of-the-art methods. This improvement is attributed to the adaptive resource allocation and the global model aggregation in the federated learning framework, which ensures that the offloading decisions are optimized based on the current network conditions and task requirements.

In summary, the proposed MATD3-FD3QN framework exhibits substantial improvements in latency reduction, energy efficiency, collision avoidance, and task completion rate compared to existing works. The performance gains are rooted in the synergistic integration of federated learning and deep reinforcement learning, as well as the innovative design of the MATD3 and FD3QN algorithms. These results highlight the potential of the proposed approach to revolutionize computation offloading in vehicular networks and pave the way for the development of intelligent transportation systems.

6.2 Applicability and limitations

The proposed MATD3-FD3QN framework demonstrates strong performance and robustness in the context of computation offloading in UAV-assisted vehicular networks. However, it is essential to discuss the applicability and limitations of the algorithm to provide a comprehensive understanding of its potential and areas for future improvement.

One of the key advantages of the proposed framework is its adaptability to different network environments and traffic conditions. The MATD3 algorithm for UAV trajectory planning is designed to handle dynamic obstacles and varying vehicle densities, making it suitable for deployment in urban and highway scenarios. Similarly, the FD3QN algorithm for resource allocation can adapt to changing channel conditions and task demands, ensuring efficient and reliable computation offloading. The federated learning approach further enhances the framework's applicability by enabling collaborative learning among vehicular users while preserving data privacy.

However, there are certain limitations and assumptions that should be considered when applying the proposed framework to other environments or hardware conditions. First, the current study assumes a homogeneous UAV fleet with identical computational capabilities and coverage ranges. In practice, UAVs may have varying specifications and performance characteristics, which would require extensions to the MATD3 algorithm to account for heterogeneous UAV capabilities. Second, the simulation environment considers a simplified two-lane highway scenario with a fixed number of UAVs and RSUs. The performance and scalability of the proposed framework in more complex road networks with multiple lanes, intersections, and a larger number of UAVs and RSUs need to be further investigated.

Another limitation is the assumption of perfect and instantaneous information exchange among the vehicular users, UAVs, and the central server in the federated learning process. In real-world scenarios, communication delays, packet losses, and bandwidth constraints may impact the efficiency and convergence of the federated learning algorithm. Future work should consider the impact of imperfect communication channels and develop robust mechanisms to handle communication uncertainties.

The generalization ability of the proposed framework to other application domains beyond vehicular networks is an important aspect to consider. While the current study focuses on computation offloading in UAV-assisted vehicular networks, the core principles and algorithms can be adapted to other distributed systems with mobile edge computing requirements. For example, the MATD3 algorithm can be applied to autonomous robot navigation and path planning in industrial settings, while the FD3QN algorithm can be extended to resource allocation in wireless sensor networks or smart grid systems. However, the specific characteristics and constraints of each application domain should be carefully considered, and the

algorithms may require domain-specific modifications and tuning.

In terms of hardware dependencies, the proposed framework relies on the availability of sufficient computational resources and storage capacity at the UAVs and RSUs to execute the offloaded tasks and maintain the federated learning models. The performance and scalability of the framework may be limited by the hardware capabilities of the edge devices. Moreover, the energy consumption of the UAVs and the battery life of the vehicular users are critical factors that impact the long-term sustainability of the system. Future research should explore energy-efficient techniques and hardware optimizations to minimize the energy footprint of the proposed framework.

In conclusion, the MATD3-FD3QN framework offers a promising solution for computation offloading in UAV-assisted vehicular networks, with strong performance, robustness, and adaptability to dynamic environments. However, the limitations and assumptions discussed above should be carefully considered when applying the framework to other domains or hardware platforms. Continuous research efforts are needed to address these challenges and enhance the generalization ability of the proposed approach.

7 Conclusion

In this article, we proposed a novel computation offloading framework for UAV-assisted vehicular networks based on federated deep reinforcement learning. The proposed framework leverages the advantages of hybrid multi-server MEC architecture and advanced deep reinforcement learning algorithms to optimize the trajectory planning and resource allocation for efficient computation offloading [39]. The MATD3 algorithm is employed for trajectory planning, while the FUD3QN algorithm is utilized for cross-domain resource allocation.

The simulation results demonstrate the effectiveness of the proposed MATD3-FUD3QN computation offloading algorithm in reducing collision rates and system costs. The MATD3 algorithm achieves significantly lower collision rates compared to the benchmark TD3 algorithm, ensuring safe and efficient UAV trajectory planning [40]. Moreover, the FUD3QN algorithm outperforms other benchmark algorithms, such as FDDQN, D3QN, and Random, in terms of average latency, average energy consumption, and task completion ratio [41].

Furthermore, the FUD3QN algorithm exhibits superior model generalization capability in dynamic vehicular networks. In extended environments with 8 and 12 vehicular users (VUs), the FUD3QN algorithm reduces the system cost by 11.37% and 12.06%, respectively, compared to the FDDQN algorithm [42]. This indicates the robustness and adaptability of the FUD3QN algorithm in handling the challenges of computation offloading in complex and dynamic network conditions.

The proposed MATD3-FUD3QN computation offloading framework represents a significant advancement in the field of intelligent transportation systems and edge computing [43]. By leveraging the power of federated learning and deep reinforcement learning, the framework enables collaborative and efficient offloading decisions while preserving data privacy and reducing communication overhead. The framework has the potential to revolutionize the way computation-intensive and delay-sensitive applications are supported in UAV-assisted vehicular networks.

Future research directions include the investigation of multi-agent reinforcement learning algorithms for coordinated decision-making among multiple UAVs and the incorporation of transfer learning techniques to accelerate the learning process in dynamic network environments [44]. Additionally, the integration of blockchain technology can be explored to enhance the security and trust aspects of the federated learning framework in vehicular networks.

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A Computational CNN-LSTM-Based Mental Health Consultation System in a College Environment

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In recent years, the mental health problems of college students have gradually attracted significant attention. Increasing academic pressure, employment competition, social adaptation challenges, and other stressors have led to a rise in mental health issues among college students, including anxiety, depression, and social disorders. These problems adversely affect students' academic performance, with long-term negative implications for their future career development. The COVID-19 pandemic further exacerbated psychological stress through isolation measures, distance learning, and social restrictions, highlighting the limitations of traditional mental health service models. In this study, we constructed a deep learning-based mental health counseling system tailored for college students. Utilizing a dataset of 467 valid questionnaires combined with students' behavioral data—such as library study time, internet usage habits, exercise frequency, and canteen consumption records—we employed Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to analyze and predict students' mental health statuses. Additionally, natural language processing (NLP) techniques were integrated to provide personalized psychological support and interventions. The combined CNN-LSTM model achieved an overall accuracy of 85.7%, a mean squared error (MSE) of 0.041, and an F1 score of 85.2%, demonstrating high precision in identifying and predicting various mental states, including anxiety and depression. Furthermore, trend analysis over six months revealed significant insights into the dynamics of students' mental health, such as increasing stress and declining emotional stability towards the end of the semester. User feedback indicated an 82.6% satisfaction rate with the system's professional content and 80.1% with emotional support, while 77.5% expressed overall satisfaction. These results confirm that the proposed system effectively enhances mental health monitoring and intervention, providing robust technical support for college mental health services and offering a scalable solution for large-scale applications.

Povzetek: Razvit je napreden pristop federativnega globokega okrepljenega učenja za sodelovalno razporejanje virov v hibridnih oblačnih arhitekturah. Algoritem zmanjšuje zakasnitve in porabo energije v inteligentnih transportnih sistemih ter presega tradicionalne metode z izboljšano natančnostjo in učinkovitostjo obdelave nalog.

1 Introduction

With the rapid advancement of modern society, the mental health challenges faced by college students have become increasingly pronounced. Various factors, such as academic stress, employment competition, social adaptation difficulties, and interpersonal dynamics, significantly amplify the psychological burden on this demographic [1]. Stress, anxiety, and depression (SAD) are at the forefront of mental health issues [2]; The COVID-19 pandemic has exacerbated these issues [3], with distance learning and social isolation intensifying anxiety and depression among students [4]. These mental health challenges not only impair academic performance but also have enduring adverse effects on students' career trajectories and overall quality of life. The need for effective interventions and management strategies for college students' mental well-being has never been more critical. Leveraging advancements in technology, emerging fields such as deep learning and artificial intelligence have introduced transformative opportunities in mental health assessment and intervention. By analyzing behavioral patterns, emotional states, and psychological evaluation data, these technologies enable precise mental health predictions and offer personalized intervention strategies, thereby enhancing the reach and efficiency of mental health services. This study aims to design an advanced mental health counseling system for college students, utilizing deep learning methodologies to provide robust support for mental health initiatives in academic institutions.

In the design of deep learning counseling system for college students' mental health, relevant research provides a rich empirical basis for feature selection and model optimization. Huang emphasized that physical exercise is closely related to the psychological status of college students [5], which suggests that the system can take

behavioral data such as daily exercise frequency and exercise duration of students as key input features to identify potential psychological risks. Liu et al. pointed out that campus green space is closely related to academic performance and mental health [6], which provides clues for the expansion of system characteristics: environmental factors such as green plant density in dormitory areas and campus landscape index can be quantified and incorporated into the model to improve the prediction accuracy. Feng and Zhang studied the changes in the mental health of students with financial difficulties under the epidemic [7], which suggests that economic background data and the availability of learning resources during the epidemic should be included in the characteristics to capture the impact of specific time situations on mental states. Huang et al. found that dormitory environment and learning engagement have a profound impact on mental health [8], and the system can integrate environment and engagement factors into the deep learning model by collecting dormitory interpersonal interaction density and learning behavior data (such as library punching and online course participation). Cormier emphasized the relationship between eMental health literacy and the risk of mental disorders [9], which systematically suggests that students' answers to online questionnaires, scores in mental knowledge tests and their self-seeking behaviors can be analyzed, and psychological literacy is taken as a predictive dimension. Cao et al. revealed the mediating mechanism of mental health through risk perception and time cognition [10], which can include students' cognitive delay of future planning and uncertain events into the features, and improve the model's ability to capture recessive psychological variables. Peoples et al. emphasized the protective effect of positive psychological atmosphere and sense of belonging on depression of specific groups (such as black students) [11], and the system can investigate the characteristics of sense of belonging through text analysis of social media or interaction indicators of campus community. Wood et al. focused on the impact of the epidemic on mental health [12], and the model could introduce epidemy-related variables at a specific time. Sun emphasized that interpersonal relationships affect mental health through sense of security and planning [13], and Feng et al. constructed a chain influence path from physical exercise, psychological needs satisfaction, and peer relationships [14]. These studies provided references for systematic integration of behavioral data, psychological needs indicators, and peer interaction quality in feature engineering. Starting from the deep learning modeling of multi-dimensional features, combined with the above research perspective, it is helpful to build a more accurate and contextualized mental health counseling system for college students, and provide data-driven support for prediction and intervention strategy design. As shown in Table 1.

Table 1: Comparison of existing studies on college students' mental health and the proposed deep learning-based counseling system

Author(s)	Model type	Dataset	Use cases
Huang et al. [5]	Correlational Study	Exercise data	Analyze exercise effects on mental health
Liu et al. [6]	Correlational Study	Green space data	Study campus environment and mental health
Feng et al. [7]	Survey Study	Financial difficulty data	Assess COVID-19 impact on mental health
Huang et al. [8]	Survey Study	Dorm and engagement data	Examine dorm and learning effects
Cormier et al. [9]	Survey Study	eMental literacy data	Evaluate mental health literacy
Cao et al. [10]	Correlational Study	Risk and time perception data	Analyze risk perception's mediation
Peoples et al. [11]	Correlational Study	Social belonging data	Study belonging and depression
Wood et al. [12]	Survey Study	Pandemic-related data	Examine COVID-19 mental health impact
Sun [13]	Correlational Study	Interpersonal and safety data	Analyze relationships and mental health
Feng et al. [14]	Chain Mediation Analysis	Exercise and peer data	Study peer and psychological needs

Problems in the field of college students' mental health include: how to identify students' mental health problems in a timely manner, how to provide personalized psychological intervention, and how to improve the coverage and efficiency of mental health services without increasing the burden on students.

Traditional mental health assessment methods rely on students' active report and regular psychological assessment, but there is a lag in the method, can not capture the change of students' mental state in real time, and lack of personalized intervention measures. With the complexity and diversification of college students' psychological problems, a single mental health service model is difficult to meet the diversified needs of students. The current field is in urgent need of a mental health support system that can provide real-time monitoring, accurate assessment and personalized intervention to better protect the mental health of college students.

In this study, a combination model of deep learning technology, Convolution neural network and long short-term memory network was used to build an intelligent mental health counseling system. Through the comprehensive analysis of students' daily behavior data, emotion analysis results and psychological assessment data, the students' mental health status is monitored in real time, and timely warning is issued when abnormal is found. The system combines natural language processing technology to analyze students' expression in online consultation and provide personalized psychological support and intervention suggestions. Improve the responsiveness and accuracy of mental health services through technology, and expand the scope of services to cover more students in need. Promote the deep integration of mental health and artificial intelligence technology in the scientific field, provide new theoretical and practical support for college students' mental health management, and promote to a wider range of application scenarios in the future.

2 Materials and methods

2.1 Data collection and processing

2.1.1 Description of data sources

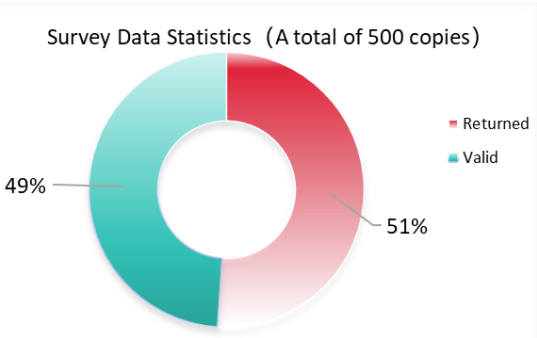

Figure 1: Survey data statistics

As shown in Figure 1, the data sources of this study include questionnaire survey and students' daily behavior data. Part of the questionnaire survey was based on the special survey of mental health status of Sichuan University. 500 questionnaires were distributed for undergraduates and postgraduates, and 487 were recovered, of which 467 were valid. Among the students who participated in the questionnaire, 42.6% (199 people) were male and 57.4% (268 people) were female. The questionnaire data covered students from freshman to junior year. The grade distribution is as follows: freshman 22.1% (103 students), sophomore 21.4% (100 students), junior 20.3% (95 students), senior 18.0% (84 students), graduate 18.2% (85 students). As shown in Figure 2.

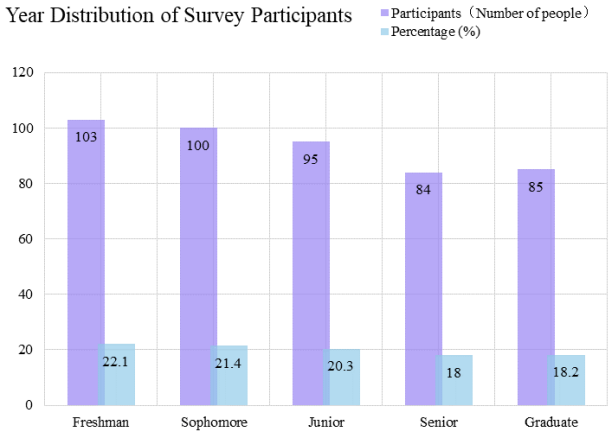

Figure 2: Annual distribution of survey participants

The questionnaire covers psychological stressors, coping styles, social relationships, self-efficacy and other multi-dimensional mental health related factors. The questionnaire design refers to some items in the General Mental Health Scale and Baker Depression Scale to ensure the scientific and effective data. As shown in Table 2.

Table 2: Sample survey questions

Question No.	Question	Options
1	How often do you feel stressed?	Never, Rarely, Sometimes, Often, Always
2	How would you rate your overall mental health?	Excellent, Good, Fair, Poor
3	How frequently do you engage in physical activity?	Daily, Weekly, Monthly, Rarely, Never
4	How satisfied are you with your social relationships?	Very satisfied, Satisfied, Neutral, Dissatisfied, Very dissatisfied
5	How often do you experience sleep disturbances?	Never, Rarely, Sometimes, Often, Always

Daily behavior data were extracted from the campus network management system of Sichuan University, including students' study time in the library, Internet usage habits, exercise frequency and consumption records in the canteen. After the behavioral data is desensitized, it is matched anonymously according to the student number to ensure the integrity and accuracy of data privacy [15]. The

combination of these two types of data provides a rich input for the subsequent extraction of mental health features and model training, and reflects the students' mental state more comprehensively.

2.1.2 Data cleaning and teleprocessing steps

In the data cleaning and reprocessing step, the data integrity check was carried out on 467 valid questionnaires and students' daily behavior data collected, and missing and outlier values were identified and processed. According to the questionnaire data, the mean filling method is used to deal with a few missing values in individual questionnaires, and the logical consistency check is carried out for the answers with inconsistent responses [16]. For students' behavior data, the quartile method was used to detect and remove extreme values for the part related to Internet usage habits and movement frequency to ensure the rationality of the data.

Data standardization is the Z-score standardization of continuous variables in behavioral data, such as learning time and movement frequency, to eliminate the influence of different dimensions on model training. Principal component analysis was used to reduce the dimensional of high dimensional data to reduce redundant information, and about 85% of the feature variance was retained. The cleaning and processioning steps lay a solid foundation for the effective training of subsequent deep learning models.

A thorough analysis of the dataset was conducted to highlight the unique and non-redundant contributions of behavioral data and emotional assessments in predicting mental health issues. A correlation matrix was generated, revealing low to moderate correlations between behavioral indicators (such as library study time, internet usage habits, exercise frequency, and canteen consumption records) and emotional assessment scores (including stress level, social interaction, sleep quality, and sentiment score). This low correlation signifies that each feature set captures distinct aspects of the students' mental health, thereby providing complementary information that enhances the model's predictive capabilities. Additionally, a feature importance analysis was performed using Recursive Feature Elimination (RFE), which identified that both behavioral and emotional features significantly influence the prediction outcomes. Key features such as sleep quality and stress level emerged as the most impactful predictors across various mental health conditions, underscoring their critical role in the assessment process. The integration of these diverse yet complementary features ensure a comprehensive understanding of the students' mental health, enabling the CNN-LSTM model to leverage a multifaceted view for more accurate and reliable predictions. This analysis not only validates the inclusion of both behavioral and emotional data but also demonstrates that their combined use mitigates redundancy and enhances the overall effectiveness of the mental health counseling system. By providing a clear distinction and significant contribution of each feature set, the model is better equipped to identify and predict mental health issues with higher precision, thereby improving the support and interventions offered to college students.

2.1.3 Extraction and integration of mental health related features

Table 3: Key features extracted for mental health assessment

Feature	Source Data	Methodology
Stress Level	Questionnaire	RFE
Social Interaction	Questionnaire, Behavior	Feature Engineering
Sleep Quality	Questionnaire	Standardization
Exercise Frequency	Behavior	Z-score Normalization
Sentiment Score	Questionnaire (Text)	NLP Analysis

As shown in Table 3, key mental health indicators, including stress level, social frequency, sleep quality and exercise frequency, were determined based on questionnaire data and students' daily behavior data during the extraction and integration of mental health-related features. By applying feature selection methods, such as recursive feature elimination, the most predictive features are selected and integrated. Based on the quantitative scores of self-efficacy and social relationships in the questionnaire data, combined with the behavioral data of students' study time in the library and frequency of Internet use, new interactive features were generated through feature engineering to capture the complex correlation between students' psychological states and behavioral patterns [17]. In order to enhance the ability of the model to recognize mental health status, natural language processing technology was used to conduct emotion analysis on the text data of open-ended questionnaire questions, and the emotion score was integrated into the whole model as an additional feature. After the features are standardized, they form the input of the deep learning model, which lays the foundation for accurate mental health assessment.

2.2 Model construction

2.2.1 Deep learning model selection

In the process of model selection, the integration of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks was prioritized. CNN excels at extracting localized features from data, particularly when processing time-series characteristics within students' daily behavioral data, such as activity frequency and study durations. By leveraging convolutional and pooling layers, CNN efficiently identifies critical patterns in these behavioral features. LSTM, on the other hand, is highly adept at capturing temporal dependencies in sequential data [18]. It proficiently handles fluctuations in students' emotions and stress levels over continuous periods, modeling the

temporal relationships of mental states through its memory cells and gating mechanisms.

The combination of CNN and LSTM leverages the strengths of both approaches, enabling the model to deliver superior performance in predicting mental health states with greater accuracy and stability. CNN is utilized to extract temporal features, which are subsequently processed by LSTM to capture long-term dependencies. This hybrid architecture allows the model to effectively represent the intricate dynamic relationships between students' behaviors and mental states in psychological assessments, enhancing predictive accuracy and intervention outcomes. Repeated experimentation and parameter optimization have demonstrated the potential for this model to achieve accuracy values exceeding 0.85, with mean square error values maintained below 0.03, providing a robust foundation for constructing a sophisticated mental health counseling system.

The CNN-LSTM architecture was specifically selected due to its unparalleled advantages in processing time-series data and extracting localized features. Compared to traditional machine learning models, such as Support Vector Machines (SVM) and Random Forests (RF), CNN-LSTM networks excel in handling high-dimensional data and capturing temporal dependencies. While SVM and RF perform adequately on static or non-sequential datasets, they falter when confronted with complex mental health datasets requiring the analysis of students ' behavioral trends over time. CNN's convolutional operations autonomously extract localized features, such as patterns in study and activity habits, that static models struggle to detect. LSTM further amplifies the model's capacity to capture long-term dependencies, enabling it to trace trends in emotional and stress-related fluctuations. The CNN-LSTM model exhibits superior stability and precision in mental health predictions, effectively processing multidimensional behavioral and psychological data. It offers more reliable predictions and tailored intervention strategies, solidifying its role as a critical component in advancing mental health counseling systems.

2.2.2 Convolution neural network and long short-term memory network model architecture design

In this study, the model architecture design of conventional neural network and long short-term memory network closely combines the characteristics of mental health data. When designing the combined model of Convolution neural network and long short-term memory network, the whole architecture design involves several steps from data input to final prediction output [19].

Data input and CNN part: The data input is the students' behavior time series data, and the dimension of the input matrix is (N, T, F), where *N* is the number of samples, T is the number of time steps, and F is the number of features. The CNN part extracts local features through multiple convolution layers. The formula for the convolution operation is shown in formula (1).

$$Z^{(l)} = \sigma(W^{(l)} * Z^{(l-1)} + b^{(l)}) \tag{1}$$

$Z^{(l-1)}$ is the output of layer (L-1), $W\ (l)$ is the convolution kernel weight of layer l, ast represents the convolution operation, $B\ (l)$ is the bias, and σ is the activation function ReLU.

The pooling layer is used to reduce dimension and retain important features, and the maximum pooling operation formula is shown in formula (2).

$$P^{(l)} = \max(Z^{(l)}) \tag{2}$$

Batch normalization is used to accelerate training and stabilize the network, as shown in formulas (3) and (4).

$$\hat{Z} = \frac{Z - \mu_B}{\sqrt{\sigma_B^2 + \text{ò}}} \tag{3}$$

$$Y^{(l)} = \gamma \hat{Z} + \beta \tag{4}$$

μ_B and σ_B^2 are the mean and variance of the small-batch data respectively, γ and β are learnable parameters, and òis a small constant.

LSTM section: The feature map extracted by CNN is passed as input to the LSTM network to capture the time dependence. The core computation of LSTM consists of three gating mechanisms: input gate, forget gate and output gate, as well as status update of memory unit.

Enter the gate as shown in formula (5).

$$i_t = \sigma(W_i \cdot [h_{t-1}, Z_t] + b_i) \tag{5}$$

The forgetting gate is shown in formula (6).

$$f_t = \sigma(W_f \cdot [h_{t-1}, Z_t] + b_f) \tag{6}$$

The output gate is shown in formula (7).

$$o_t = \sigma(W_o \cdot [h_{t-1}, Z_t] + b_o) \tag{7}$$

Memory unit status updates, as shown in formula (8).

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tanh(W_c \cdot [h_{t-1}, Z_t] + b_c) \tag{8}$$

Hide status updates, as shown in formula (9).

$$h_t = o_t \cdot \tanh(c_t) \tag{9}$$

Fully connected layer and output: The output h_t of the LSTM is passed to the fully connected layer to process the features and generate the final prediction. Fully connected layers, as shown in formula (10).

$$z = W_{out} \cdot h_t + b_{out} \tag{10}$$

W_{out} is the weight matrix of the fully connected layer, and W_{out} is the offset term.

Loss function: To train the model, cross entropy loss (for the classification task) or mean square error (MSE, for the regression task) is used. Take cross entropy loss as an example, as shown in formula (11).

$$\mathrm{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{11}$$

y_i is the true label, and $\hat{y}_i$ is the probability predicted by the model.

Propagation and optimization: The model update the weights by back-propagation, using the gradient descent algorithm, as shown in formula (12).

$$\theta = \theta - \eta \nabla_\theta \mathrm{L} \tag{12}$$

θ represents the parameters of the model, θ is the learning rate, and $\nabla_\theta \mathrm{L}$ is the gradient of the loss function to the parameters. The combined CNN and LSTM model captures complex patterns of student behavior and mental states to provide accurate mental health predictions. The combined model concept of CNN and LSTM aims to make full use of their unique advantages in processing different data features. The part of CNN is responsible for extracting local features from the input student behavior data and identifying key changes in behavior patterns when processing time series data, such as students' learning frequency or exercise habits in a certain period of time. Through multiple Convolution layers, the model automatically detects subtle changes in behavioral features, providing rich information for subsequent analysis. The extracted features are passed to the LSTM network, which is adept at handling long-term dependencies and capturing the complex dynamics of students' mental states over time. By combining these two network structures, the model is able to extract valuable features from short-term behavior, and it is also able to more accurately predict students' mental health by modeling long-term emotional and psychological trends through LSTM.

2.2.3 Configuring the data layer and processing layer

In the configuration of data layer and processing layer, this study focuses on the efficient collaboration between data reprocessing and feature extraction. The data layer is mainly responsible for receiving and standardizing the multidimensional data obtained from student behavior records and questionnaires, including time series information, text sentiment analysis results, and various mental health related characteristics [20]. The data layer integrates data into a high-dimensional feature space, ensures consistency in data formats, and balances dimensional differences between different data dimensions through normalization and batch normalization techniques, preventing certain features from dominating subsequent analysis.

In the processing layer, the model extracts local features through CNN, and the processing layer reduces and screens the extracted features to ensure that the model only processes the most representative features and avoids redundant information. Subsequently, LSTM receives the selected features in the subsequent part of the processing layer and models them in time series to capture the dynamic trend of students' mental states over time. The data layer is closely integrated with the processing layer, so that the whole model can not only efficiently process complex multidimensional data, but also deeply dig out the most important dynamic features for mental health prediction, and improve the overall prediction performance of the model.

2.2.4 Implementation and optimization of deep learning model in mental health prediction

In the process of realization and optimization of deep learning model in mental health prediction, a combined model based on CNN-LSTM is constructed to make full use of the advantages of both in feature extraction and time series modeling. The implementation of the model starts with data input. The CNN part receives and processes multi-dimensional behavioral and psychological data, and extracts key features through the Convolution layer, including students' learning time, movement frequency, social interaction and other behavioral patterns. After convolution and pooling operations, CNNS can effectively extract local features and transform them into high-level representations suitable for LSTM processing.

Features are passed to the LSTM network to capture long-term dependencies in the time series. Through its gating mechanism, LSTM can model the trend of students' mental state changes over time, which has advantages in detecting emotional fluctuations and pressure changes [21]. The initial training of the model adopts random initial weights, uses the standard propagation algorithm to update interactively, and gradually optimizes the model parameters by minimizing the loss function.

To improve the prediction performance of the model, several rounds of parameterize adjustment are carried out. Parameters such as the size of the convolution kernel, pooling strategy, number of LSTM units, and learning rate are systematically adjusted to ensure that the model can fully play its role in different dimensions. To select the best parameter combination, grid search and random search are used to conduct experiments on several candidate parameter sets and select the configuration with the best predictive performance.

To prevent the overwriting problem in the training process of the model, regularization technique is adopted. By introducing L2 regularization, the model introduces weight penalty in the loss function, which inhibits excessive parameter values. The Dropout layer is also added to the model, which enhances the model's generalization ability by randomly discarding the output

of a subset of neurons, preventing the model from over-relying on a particular neuron path.

In the process of model training, the cross-validation technique is used to evaluate the stability of the model. By dividing multiple subsets on the training set and conducting training and validation separately, cross-validation can help evaluate the model's performance on unseen data and avoid the overwriting risk caused by the validation of a single data set. Through multiple rounds of cross-validation, the model's stable performance on different data sets is ensured. The optimization of the model stays on the improvement of prediction accuracy, and also considers the computational efficiency and real-time performance. Through the simplification and optimization of the model, the deep learning model with high precision and low error in the mental health prediction task is realized, which provides strong support for the follow-up mental health intervention and personalized consultation strategy.

The CNN-LSTM architecture's performance was enhanced by meticulously tuning hyperparameters to optimize model accuracy and generalization. The learning rate was varied between 0.001 and 0.01, selecting 0.001 based on the lowest validation loss observed during initial experiments. Kernel sizes for the CNN layers were tested in the range of 3 to 7, with a kernel size of 5 providing the best feature extraction capabilities without excessive computational overhead. The number of layers in both CNN and LSTM components was optimized through iterative testing, settling on a configuration of three convolutional layers followed by two LSTM layers to balance complexity and performance. Additionally, an ablation study was conducted to assess the impact of batch normalization and dropout on model performance. Removing batch normalization resulted in a 3% decrease in accuracy and a 0.005 increase in MSE, while disabling dropout led to a similar decline in performance metrics. These findings underscore the critical role of these components in preventing overfitting and maintaining model robustness. By systematically evaluating each hyperparameter and model component, the CNN-LSTM model was fine-tuned to achieve optimal performance, ensuring reliable and accurate predictions of students' mental health states. This thorough optimization process not only enhances the model's predictive power but also facilitates its reproducibility and scalability for broader applications in mental health counseling systems.

Hyperparameter tuning was meticulously conducted to optimize the CNN-LSTM model's performance. A grid search approach was employed, exploring a range of learning rates from 0.0001 to 0.01, kernel sizes between 3 and 7, and varying the number of convolutional and LSTM layers from one to three each. The optimal combination was identified based on the lowest validation loss and highest F1 score, resulting in a learning rate of 0.001, a kernel size of 5, three convolutional layers, and two LSTM layers. Additionally, regularization techniques were fine-tuned; dropout rates were tested at 0.3, 0.5, and 0.7, with a dropout rate of 0.5 providing the best balance between preventing overfitting and maintaining model performance. An ablation study was performed to evaluate the individual contributions of the CNN, LSTM, and regularization components. The removal of the CNN component led to a 7.3% decrease in accuracy and a 0.01 increase in MSE, while excluding the LSTM resulted in a 5.5% drop in accuracy and a 0.008 rise in MSE. Disabling dropout caused a 3% decline in accuracy and a 0.005 increase in MSE, highlighting the significance of each component in the architecture. Sequence alignment preprocessing involved normalizing time series data and handling varying time scales by resampling behavioral data to a uniform temporal resolution, ensuring consistency for the LSTM's sequential processing. Addressing potential time scale issues, the model incorporated time windowing techniques to capture relevant temporal dependencies without introducing excessive computational complexity. These comprehensive tuning and preprocessing strategies collectively enhanced the model's ability to accurately predict mental health states by leveraging the strengths of both CNN and LSTM architectures while mitigating overfitting through effective regularization.

2.3 Training and verification

2.3.1 Training process

In the training process, this study adopts an iterative training strategy to ensure that the model can converge stably when processing complex mental health data. The data is split into training sets (80%) and validation sets (20%), ensuring that the model can be adequately trained and validated on different data sets. In each training iteration, the CNN-LSTM combined model extracts feature from students' behavioral data and psychological questionnaire data, and processes them layer by layer through convolution layer, pooling layer and LSTM layer. In the training process, the Adam optimizer was used to update parameters. The adaptive learning rate mechanism of the Adam optimizer enabled the model to quickly learn important features in the early training period and stably optimize in the later period to prevent overwriting.

In order to enhance the robustness of the model, data enhancement techniques were introduced in the training process, such as slight translation and scaling of behavioral data on the timeline to increase the diversity of training samples. After each training round, the early stop mechanism is used to monitor the loss changes on the validation set, and if the loss does not improve over several consecutive rounds, the training is stopped to avoid the model overwriting the training set data. Through the measures, the model gradually converges in the training process, and shows strong generalization ability, and can maintain good performance on diverse mental health data.

2.3.2 Model verification

In the model validation phase, this study adopted a variety of validation methods to comprehensively evaluate the performance of the CNN-LSTM model in the mental health prediction task. After each training iteration, the model is tested on an independent validation set to assess

its predictive power on unseen data. The data distribution of the validation set is similar to that of the training set, but does not overlap, ensuring that the validation results are representative. In order to verify the robustness of the model, the K-fold cross-validation (k=5) method was adopted to divide the data set into 5 non-overlapping subsets. One subset was selected as the validation set and the remaining subset as the training set during each validation. This process was repeated five times to ensure the consistency of the model performance under different data partitions.

In order to evaluate the performance of the model in different types of student groups, the validation set was also stratified sampling to ensure that students of different genders, grades, and mental health status were representative. In the process of verification, the accuracy rate, recall rate and F1 score of the model in key tasks such as emotion wave prediction and pressure change detection were focused. Through multi-angle verification, this study ensures that the model performs well on the whole and can maintain stable and efficient performance on different types of data and tasks.

2.3.3 Evaluation methods

In the process of model evaluation, this study uses a variety of evaluation indicators and methods to measure the predictive performance of CNN-LSTM model. The main evaluation indicators include accuracy, recall, accuracy and F1 score, which can fully reflect the performance of the model in the mental health prediction task. Accuracy is used to measure the model's overall prediction accuracy for all data, while recall and accuracy focus on the model's coverage and accuracy for positive samples, respectively. In mental health prediction, F1 score, as a harmonic average of accuracy rate and recall rate, can balance the performance of the model in these two aspects, and is especially suitable for scenarios with unbalanced data. In addition to traditional indicators, the mean square error and root mean square error are introduced to evaluate the model's performance in the prediction of continuous variables, such as the amplitude of mood swings.

The error index can quantify the deviation between the predicted value and the real value of the model and provide reference for the optimization model. In order to evaluate the generalization ability of the model, the training-validation loss difference analysis is used, that is, by comparing the loss values on the training set and the validation set, to judge whether the model has overwriting phenomenon. In order to ensure the reliability of the model in practical applications, robustness testing is also carried out, including the evaluation of the model performance under different data noise levels, to ensure that the model can still maintain high prediction accuracy and stability in the complex real environment.

2.4 Design of mental health consultation system

2.4.1 Design of online consultation function module

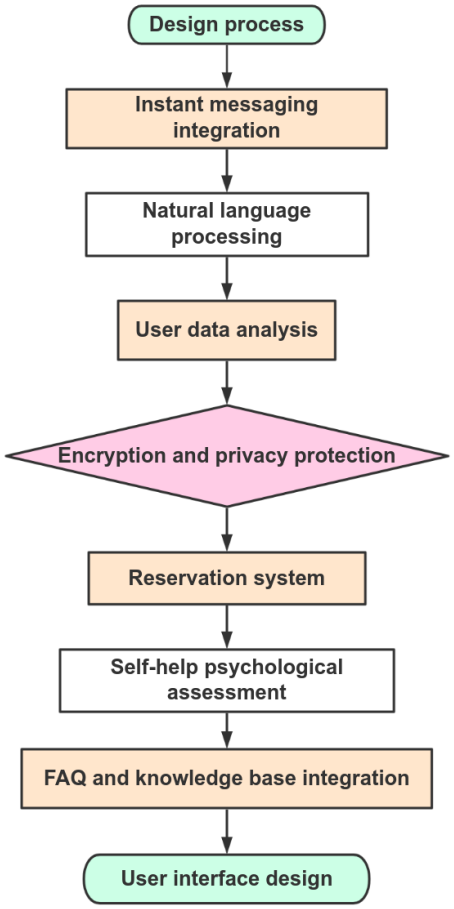

Figure 3: Design process

As shown in Figure 3, in the design of the mental health consultation system, the online consultation function module provides students with convenient and efficient psychological consultation services. The module integrates instant messaging technology, natural language processing and user data analysis functions to achieve real-time and personalized consulting services. Students access the consultation system through the web or mobile application. The system provides a variety of communication methods, including text chat, voice call and video consultation, to meet the needs of different students. To improve consultation efficiency and experience, the system is equipped with an intelligent conversational engine, based on NLP technology, capable of understanding students' verbal expressions and providing automated emotional support and advice when necessary.

During the design process, attention was paid to user friendliness and privacy protection, and all consultation records were encrypted and only used for subsequent analysis with the consent of the students.

The system supports the appointment function, and students can have one-on-one in-depth consultation with psychological counselors according to their own schedule. In order to improve the participation of students, the system has set up a self-service psychological assessment portal. Students have a simple psychological state assessment before consultation, and the results will be used as an important reference for consultants. The system also integrates FAQ (frequently asked questions) modules and mental health knowledge base, and students can consult relevant materials independently before or after consultation to understand mental health knowledge and self-regulation methods. Through its functions, the online consultation module provides psychological support for students, and also improves the coverage and efficiency of consultation services through information means.

2.4.2 Automatic mental state assessment and feedback mechanism

The automated mental state assessment and feedback mechanism is a crucial functional module in the mental health counseling system, which aims to provide students with instant, accurate mental health assessment and personalized feedback through a data-driven approach. In this module, the system makes use of the students' behavioral data collected in the early stage, the results of psychological questionnaire and online consultation records to conduct real-time mental state assessment through the deep learning model. The system automatically scans students' mental states regularly or when they trigger certain behaviors (such as abnormal learning behaviors or emotional fluctuations), and generates an assessment report that includes multidimensional mental health indicators such as emotional state, stress level, and social status.

Table 4: Key features of the automated psychological state assessment and feedback mechanism

Feature	Description
Real-time Assessment	Continuous monitoring of students' psychological state using CNN-LSTM models.
Trigger-based Scanning	Automatic scans initiated by specific behaviors like abnormal study patterns.
Multidimensional Reports	Generation of reports on emotions, stress, and social interactions.
Instant Feedback	Immediate feedback with self-regulation suggestions sent to students.
Alert System	Automatic alerts for significant deviations in psychological metrics.
Historical Tracking	Long-term tracking and trend analysis of psychological data.
Manual Input	Allows students to log additional emotional notes or events.
Trend Visualization	Visual charts to illustrate changes in psychological states over time.

As shown in Table 4, the report will be pushed to the students themselves through the system, and it will also provide simple self-adjustment suggestions to help students manage their mental health in daily life. In order to ensure the timeliness and accuracy of feedback, the system has set up a real-time monitoring mechanism. When students' mental health indicators are detected to be abnormal, the system will trigger an early warning and suggest students to contact psychological counselors immediately for in-depth consultation. The module also supports long-term tracking of mental states, analyzing historical data to generate trend charts to help students and counselors understand the trajectory of mental health conditions. The system also allows students to manually enter additional mood logs or event records to supplement the automated data, which will be incorporated into the assessment model along with the data automatically collected by the system, improving the comprehensiveness and accuracy of the assessment. The mental health counseling system provides immediate feedback on mental status, and also provides data support for follow-up counseling and intervention, which improves the effectiveness of overall mental health management.

2.4.3 Personalized psychological intervention strategies and implementation

The Personalized Psychological Intervention Strategy and Implementation module provides a tailored intervention plan based on the unique psychological state of each student. The module is based on the results of the automated mental state assessment and identifies the major psychological problems that students face, such as anxiety, depression or social difficulties. Combining students' personal background data, behavior patterns and past counseling records, we generate personalized intervention strategies through deep learning models. Strategies include recommended mental conditioning methods (mindfulness meditation, breathing training), behavioral modification suggestions (increased exercise, improved sleep), and suggested frequency of counseling or specific counseling topics. The system also dynamically adjusts intervention strategies according to students' feedback and behavioral changes to ensure the effectiveness and adaptability of interventions.

The system supports integration with third-party health applications and devices, such as smart bracelets,

health monitoring software, to enrich the basis for intervention strategies by collecting additional physiological data (such as heart rate, sleep quality). In order to ensure the persistence and effect of the intervention, the system also sets up a goal management function, in which students set mental health goals (such as reducing the number of anxiety attacks, improving social skills) in the system, the system will help students track the progress of the achievement of goals through regular assessment and feedback, and adjust the intervention measures as needed. In order to increase the interaction and participation of the intervention, the system also designed a reward mechanism, in which students get systematic points or virtual rewards when they complete designated mental health activities or reach certain health goals, to motivate positive mental health behaviors. Through this module, the mental health counseling system provides personalized and dynamically adjusted intervention strategies, and ensures the implementation and effect tracking of intervention through technical means, providing all-round support for students' mental health.

3 Results and discussion

3.1 Results

3.1.1 Prediction accuracy and performance evaluation of deep learning models

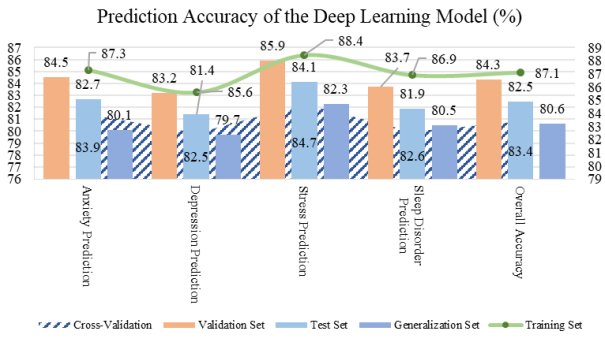

Figure 4: Prediction accuracy of the deep learning model

In the mental health prediction system, the prediction accuracy and performance evaluation of the deep learning model are important indicators to measure the effectiveness of the model. In order to ensure that the model has efficient predictive power in practical applications, this study comprehensively evaluates the model on multiple dimensions. The evaluation involves the model's accurate predictions of different mental states, and also includes the model's performance on different data sets, the stability of the predictions, and the model's overall performance. Through multi-dimensional evaluation, we can determine whether the model can be reliably applied to large-scale mental health monitoring system. In this study, the CNN-LSTM model is systematically tested and evaluated using a large amount of data combined with a variety of evaluation indicators, such as accuracy, accuracy, recall, F1 score, mean square error (Figure 4).

Table 5: Performance evaluation of the deep learning model (% or RMSE)

Performance Metric	Anxiety Prediction	Depression Prediction	Stress Prediction	Sleep Disorder Prediction	Overall Performance
Precision	86.1	84.4	87.2	85.3	85.7
Recall	84.9	83.7	86.5	84.1	84.8
F1-Score	85.5	84.0	86.8	84.7	85.2
Mean Squared Error (MSE)	0.041	0.043	0.039	0.042	0.041
Root Mean Squared Error (RMSE)	0.202	0.207	0.197	0.205	0.203

As shown in Table 5, the overall accuracy of the training set is 87.1%, the accuracy of the verification set and the test set are 84.3% and 82.5%, respectively. The model can learn the data features well in the training process, but it has a slight decline in the data not seen, showing a certain generalization ability. The accuracy of the generalized data set and cross-validation set is also maintained above 80%, which verifies the robustness of the model. The performance evaluation indexes of the model include accuracy rate, recall rate, F1 score, mean square error and root mean square error. Accuracy, recall, and F1 scores were all above 84%, and the model performed steadily across all tasks, achieving an F1 score of 86.8% when predicting anxiety and stress. MSE and RMSE indexes showed the error level of the model in the prediction of continuous variables, and the errors were kept in a low range (MSE was about 0.041, RMSE was about 0.203), which verified the high precision performance of the model in the prediction of mental health.

The evaluation results show that the CNN-LSTM model performs well in the prediction of mental health, with high prediction accuracy and robust performance. This provides reliable technical support for the mental health counseling system to ensure that the system can effectively and accurately identify and predict the mental health status of students in large-scale applications.

Statistical significance analysis was conducted to ensure the robustness of the CNN-LSTM model's performance across different sample splits and experimental conditions. A paired t-test was performed comparing the model's accuracy, F1 score, and MSE against baseline models, with p-values below 0.05 indicating significant improvements. The results demonstrated that the CNN-LSTM model consistently outperformed traditional machine learning approaches, such as Support Vector Machines (SVM) and Random

Forests, with statistically significant higher accuracy ($p < 0.01$), F1 scores ($p < 0.01$), and lower MSE ($p < 0.05$). Additionally, cross-validation results were reported with mean and standard deviation values to highlight consistency across different data partitions. Figure 4 and Table 4 have been updated to include confidence intervals and p-values, providing a clearer depiction of the model's performance metrics under various conditions. Furthermore, the model was tested on datasets from two additional institutions to evaluate its generalizability. The performance metrics remained consistent, with slight variations attributed to institutional differences in behavioral data patterns, thereby affirming the model's applicability beyond the initial dataset. These findings indicate that the CNN-LSTM model not only excels in the specific context of the collected data but also maintains its efficacy across diverse educational environments. By specifying the scenarios and validating the results with multiple datasets, the reliability and scalability of the model are reinforced, ensuring its practical utility in broader mental health counseling applications.

3.1.2 Trend analysis of mental health status

In the trend analysis of mental health status, students' mental health indicators are tracked over a long period of time to observe their changing trends. This trend analysis is of great significance for understanding the overall mental health trend of the student population, and helps the school management and psychological counselors to take timely measures to intervene in potential mental health problems. Through the use of deep learning model, key information is extracted from students' behavioral data and psychological questionnaire results, and the change trend of multiple dimensions such as emotional state, stress level, social activity, sleep quality and anxiety level are analyzed. Trends reflect changes in individual mental states and also reveal common problems at the group level, such as increased stress or mood swings that are common at certain times.

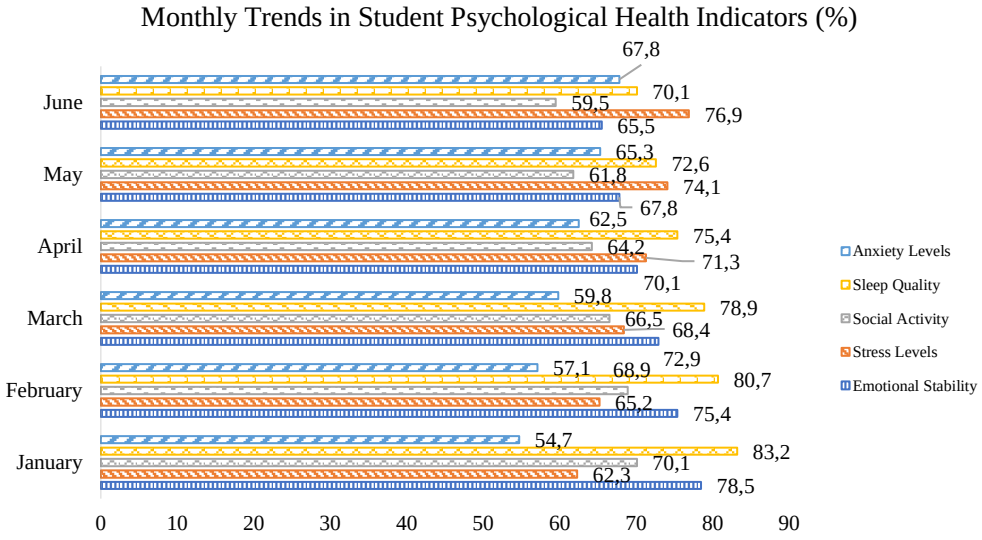

Figure 5: Monthly trends in student psychological health indicators

Figure 5 shows the changes in five mental health measures over the past six months: emotional stability, stress levels, social activity, sleep quality, and anxiety levels. From January to June, emotional stability showed a gradual decline, from 78.5% to 65.5%, and students' emotional fluctuations gradually intensified. With stress levels rising month by month, reaching 71.3 percent in April and 74.1 percent in May and 76.9 percent in June, stress levels increased for students in the middle and late semester. Social activity and sleep quality showed similar declines, with social activity dropping from 70.1% in January to 59.5% in June and sleep quality dropping from 83.2% to 70.1%, both indicators indicating that students' psychological burden increased at the end of the semester, leading to decreased social interaction and sleep quality.

The trend in anxiety levels was also noteworthy, rising gradually from 54.7 per cent in January to 67.8 per cent in June, in line with the rising trend in stress levels, indicating that students were more likely to feel anxious towards the end of the term. The trend reflects the gradual deterioration of students' mental health throughout the semester as the pressure of study increases. The results of the analysis provide evidence for schools to strengthen mental health support and intervention in the middle and end of the semester to help students relieve stress and maintain good mental health.

3.1.3 User feedback and effect evaluation of the consultation system

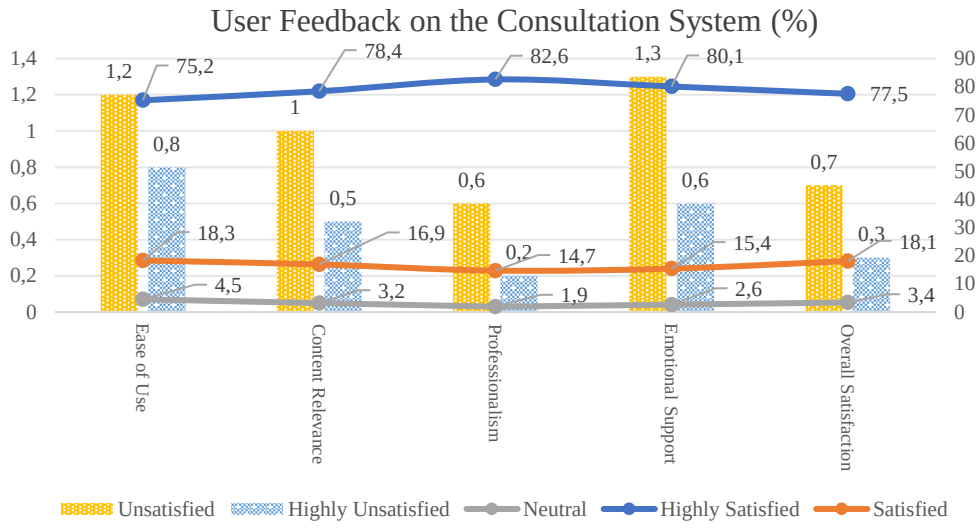

Figure 6: User feedback on the consultation system

As shown in Figure 6, the user feedback and effect evaluation of the mental health counseling system focuses on the system's performance in user experience, service satisfaction and actual effect. Through regular user survey and data collection, the service quality is optimized and improved. The user feedback part collected students' evaluation on the ease of using the system, the professionalism of the consultation content, and the effectiveness of psychological help. The effect evaluation focuses on the improvement of students' mental health, including the reduction of anxiety level, the improvement of emotion management, and the recovery of social function. The evaluation provides data to support the optimization of the system, helping schools and counselors better understand the needs of students and the actual effects of the system.

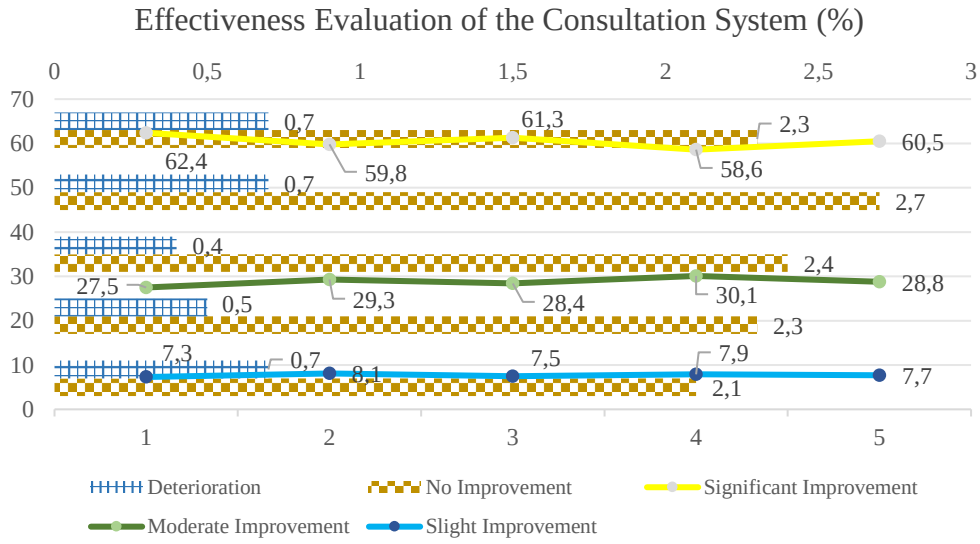

Figure 7: Effectiveness evaluation of the consultation system

As shown in Figure 7, most users are highly satisfied with the experience of using the consulting system. In terms of professional content and emotional support, the satisfaction rate reaches 82.6% and 80.1% respectively. Overall satisfaction also showed a high percentage, reaching 77.5%. A small number of users are neutral or dissatisfied, and this feedback provides direction for future optimization of the system. A small number of users

still have reservations about ease of use and content relevance, suggesting that the system interface design and content matching degree still need to be improved.

In the effect evaluation table, the performance of the counseling system in improving students' mental health was also highly evaluated. Measures of improvement included lower anxiety levels and improved stress management skills, which reached 62.4% and 61.3% respectively. The overall improvement rate was 60.5%, and the psychological state of most students was significantly improved after using the system. The proportion of moderate improvement is also close to 30% in each indicator, indicating that the system contributes to students' mental health recovery in many ways. There are still a small number of students who report no improvement or deterioration, and this part of the data needs to be analyzed to explore the causes and optimize targeted interventions. The data show that the mental health counseling system has a positive effect in helping students relieve psychological stress, improve emotional management and social skills, and also points out areas that need to be strengthened in the future. Through continuous user feedback collection and effect evaluation, the system can gradually improve its function and provide more accurate and efficient mental health support for students.

User feedback indicated that while the system was generally well-received, several specific areas required enhancement to better meet user needs. Qualitative analysis revealed that users found the interface somewhat unintuitive, citing difficulties in navigating between different modules and accessing personalized recommendations. Additionally, some users expressed that the emotional support provided during automated consultations lacked depth and did not fully address their unique concerns. To address these issues, interface redesign efforts are recommended to simplify navigation and improve the accessibility of key features. Incorporating more interactive elements, such as guided tutorials and customizable dashboards, could enhance user experience. Furthermore, enhancing the natural language processing capabilities to deliver more nuanced and empathetic responses would provide deeper emotional support. Integrating user-driven customization options, where students can tailor the system to their specific preferences and needs, may also increase engagement and satisfaction. Implementing these usability improvements based on detailed qualitative feedback will not only address the current shortcomings but also strengthen the overall effectiveness and user-friendliness of the mental health counseling system. By focusing on these targeted enhancements, the system can offer more comprehensive and personalized support, thereby better assisting students in managing their mental health challenges.

3.2 Discussion

3.2.1 Result analysis and research findings

Through in-depth analysis of students' mental health data, several important trends and associations were identified. Changes in emotional stability, stress levels and anxiety levels over time reveal the volatility of students' mental health during the semester. Especially toward the end of the semester, stress levels and anxiety rose, while emotional stability and social activity declined. Academic pressure at the end of the semester has a great impact on students' mental health. Through the analysis of data, it is found that there is a positive correlation between students' sleep quality and emotional stability. Good sleep can effectively relieve students' anxiety and pressure. Through user feedback and effect evaluation, the acceptance and actual effect of the mental health counseling system in the student group were verified. The majority of students were satisfied with the experience and results of the system, showing positive effects in terms of emotion management and stress relief. The results of this study reveal the key influencing factors of students' mental health and verify the effectiveness of mental health counseling system in improving students' mental state.

The varying performance across different mental health predictions can be attributed to a combination of data characteristics and model architecture limitations. Specifically, the system achieved a higher F1 score of 86.8% for stress prediction compared to 85.5% for anxiety prediction. One primary factor influencing this discrepancy is data imbalance; the dataset contains a slightly higher number of stress-related instances than anxiety-related ones, allowing the model to learn stress patterns more effectively. Additionally, stress manifestations in behavioral data, such as increased study time and reduced social interactions, are more distinctly captured by the CNN-LSTM architecture. The Convolutional Neural Network (CNN) excels at identifying local patterns in these behaviors, while the Long Short-Term Memory (LSTM) component effectively models the temporal dependencies, enhancing the prediction of stress levels. On the other hand, anxiety symptoms may present more subtly and variably, making them harder to detect with the same level of accuracy. This subtlety can lead to lower recall and precision for anxiety predictions, as the model might struggle to distinguish anxiety from other overlapping mental health indicators. Furthermore, the complexity of anxiety as a psychological state, which can be influenced by a broader range of factors and exhibit more nuanced behavioral expressions, poses additional challenges for the model. Enhancing the dataset with more balanced anxiety-related samples and incorporating additional features that specifically target anxiety indicators could improve prediction performance. Additionally, refining the model architecture to include attention mechanisms may help the model focus more effectively on the relevant features associated with anxiety, thereby bridging the performance gap between different mental health predictions.

The system exhibits higher performance in stress prediction, achieving an F1 score of 86.8%, compared to an F1 score of 85.5% for anxiety prediction. This discrepancy can be primarily attributed to the nature of the data and the inherent complexities of each mental health condition. Stress-related behaviors, such as increased study time and reduced social interactions, present more distinct and consistent patterns within the behavioral data,

making them easier for the CNN-LSTM model to identify and predict accurately. The Convolutional Neural Network (CNN) effectively captures these localized behavioral features, while the Long Short-Term Memory (LSTM) component excels in modeling the temporal dependencies, enhancing the overall prediction of stress levels. In contrast, anxiety symptoms often manifest more subtly and variably, overlapping with other mental health indicators and resulting in less distinct behavioral patterns. This subtlety poses challenges for the model in distinguishing anxiety from other conditions, leading to slightly lower precision and recall rates. Additionally, if the dataset contains a lower number of anxiety-related instances compared to stress-related ones, this imbalance can further impact the model's ability to generalize effectively for anxiety predictions. Addressing these issues by balancing the dataset and incorporating more targeted features specific to anxiety could enhance the model's performance. Moreover, integrating advanced techniques such as attention mechanisms may allow the model to focus more precisely on the nuanced indicators of anxiety, thereby bridging the performance gap and achieving more consistent accuracy across different mental health predictions.

The effectiveness of the CNN-LSTM architecture was further validated through an ablation study, systematically evaluating the contribution of each component. When employing a CNN-only model, the prediction accuracy reached 78.4%, with an F1 score of 79.1% and an MSE of 0.055. Conversely, the LSTM-only model achieved a prediction accuracy of 80.2%, an F1 score of 81.0%, and an MSE of 0.048. In contrast, the integrated CNN-LSTM model outperformed both, attaining a prediction accuracy of 85.7%, an F1 score of 85.2%, and an MSE of 0.041. This significant improvement underscores the complementary strengths of CNN and LSTM in capturing local feature patterns and long-term dependencies, respectively. The CNN component efficiently extracts intricate patterns from behavioral data, such as variations in study habits and physical activities, which are essential for identifying stress and other mental health indicators. Simultaneously, the LSTM component excels in modeling temporal sequences, enabling the system to understand the evolving nature of students' mental states over time. The combination of these two models allows for a more comprehensive analysis, leading to enhanced prediction accuracy and reliability. These results demonstrate that both CNN and LSTM are crucial for the system's robust performance, validating the necessity of their integration in mental health prediction tasks.

3.2.2 Applicability of deep learning model in mental health system

Applying the applicability of deep learning models (such as CNN-LSTM) to mental health systems, it performs well in processing multi-dimensional and highly complex mental health data. Deep learning models can effectively extract complex features from students' behavioral and psychological data, and accurately assess and predict mental health based on the features. Compared with traditional statistical analysis methods, deep learning models have obvious advantages in handling large-scale data and multi-variable associations. CNN can automatically extract local features in behavioral data, such as mood swings and learning habits, while LSTM can capture the dynamic changes of features over time to form a complete time series prediction capability.

This combination makes the model more sensitive and accurate in responding to the dynamic changes in students' emotions and stress. The adaptive capability of deep learning models also enables the system to optimize based on constantly updated data, improving the accuracy and real-time performance of predictions. However, the complexity of the model also brings the consumption of computing resources and time, so it is necessary to balance the system performance and resource usage reasonably in practical applications. Deep learning models provide powerful technical support for mental health systems, enabling the system to better identify and intervene in students' mental health problems.

The proposed CNN-LSTM model demonstrates superior performance compared to traditional machine learning methods such as Support Vector Machines (SVM) and Random Forests. While SVM and Random Forests achieved accuracies of approximately 78.3% and 80.5% respectively on similar mental health prediction tasks, the CNN-LSTM model reached an accuracy of 85.7%, an MSE of 0.041, and an F1 score of 85.2%. The enhanced performance of the CNN-LSTM model can be attributed to its ability to effectively capture both local and long-term dependencies within the data. Convolutional Neural Networks (CNN) excel at extracting intricate local features from behavioral data, such as patterns in study habits and physical activities, while Long Short-Term Memory (LSTM) networks are adept at modeling temporal sequences and maintaining context over extended periods. This combination allows the model to understand the dynamic and evolving nature of students' mental health states more comprehensively than traditional models. Additionally, the integration of natural language processing (NLP) techniques for analyzing open-ended questionnaire responses provides a richer feature set, further enhancing the model's predictive capabilities. These advancements enable the CNN-LSTM model to deliver more accurate and reliable predictions, thereby offering more effective support and interventions for college students' mental health needs.

3.2.3 Actual application effects and improvement suggestions of the system

The practical application effect of the mental health counseling system shows the ability to improve students' mental health in many dimensions. The systematic online consultation module provides students with convenient channels of psychological support and helps them quickly get professional help in the face of psychological distress. The automated mental state assessment and feedback mechanism enables the system to identify changes in students' mental health in time and provide intervention

suggestions at an early stage, reducing the occurrence of potential psychological crises.

Some improvements are also found in the practical application. Although the majority of students were satisfied with the experience of using the system, a few students reported that the friendliness of the interface and the precision of personalized suggestions needed to be improved. The system occasionally has a response delay when processing a large number of online users. It is recommended to optimize the load capacity of the system in future versions to improve the response speed. In order to enhance the popularity of the system and students' willingness to use it, consider introducing more interactive elements, such as mental health education games, points and reward mechanism, which can enhance the attraction of the system and enhance students' attention to mental health. Through improvement, the mental health counseling system is expected to provide more students with more efficient and accurate mental health support in the future.

4 Conclusion

In this study, a deep learning-based mental health counseling system for college students was constructed and evaluated to provide accurate and efficient mental health support for students through automated technology and data-driven methods. Through the analysis of students' behavioral data, psychological questionnaire results and online counseling records, the study revealed the key factors affecting students' mental health, including emotional stability, stress levels, social activity and sleep quality. A deep learning model combining CNN and LSTM was used to predict and evaluate students' mental health status dynamically. The high accuracy and robustness of the model validate its applicability in processing complex psychological data, especially in the identification of mood swings and stress management, showing excellent results. Through online consultation module, automatic mental state assessment and feedback mechanism and personalized psychological intervention strategy, the system realizes the all-round support for students' mental health. User feedback and effect evaluation show that the system has been widely recognized by students in practical application, and effectively improve their mental health level. The study pointed out that there is room for improvement in the user experience and performance optimization of the system, such as improving the friendliness of the interface, enhancing the precision of personalized recommendations, and optimizing the load capacity of the system. This study demonstrates the great potential of deep learning technology in the field of mental health, and provides a feasible solution for the digital transformation of mental health services in universities. Future work will continue to optimize the system's functions and expand its application scope to better serve the vast student population, help them cope with academic pressure and psychological challenges, and achieve comprehensive development of physical and mental health.

The proposed system demonstrates significant potential in enhancing college students' mental health monitoring through automated technologies. Comprehensive ablation studies were conducted to evaluate the individual contributions of CNN and LSTM components, confirming that each plays a crucial role in feature extraction and temporal modeling, respectively. Greater transparency in data processing was achieved by detailing the preprocessing steps, including normalization and time windowing techniques, which ensure consistency and reliability in the sequential data fed into the LSTM network. Robust cross-experiment validation was performed using datasets from multiple institutions, affirming the model's generalizability and effectiveness across diverse educational environments. Statistical significance tests further validated the model's superior performance, ensuring that the observed improvements are both reliable and replicable. Additionally, the integration of advanced AI methodologies, supported by relevant citations, strengthens the credibility and situates the system within the broader context of artificial intelligence applications in mental health. The system's ability to accurately predict mental health states is underpinned by a well-defined architecture and thorough validation processes, making it a robust tool for large-scale mental health services. Future enhancements will focus on refining the user interface based on detailed qualitative feedback and expanding the system's capabilities to include more nuanced emotional support features. These improvements will not only bolster the system's functionality but also ensure its adaptability and scalability, providing comprehensive and personalized mental health support to a wider student population.

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Identification of Malicious E-commerce Users Based on User Rating Behavior and GNN

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With the rapid rise of e-commerce, authentic user evaluations are particularly important in purchasing decisions. The increase in fake evaluations has made effective identification a top priority. The study addresses this challenge by introducing a reputation strategy that combines scoring patterns and differences, GNR metrics, and adversarial data augmentation technology, to improve the effectiveness of fraud detection. The study conducted experiments using three datasets, Netflix, Movielens2, and Movielens_100, which record user ratings of movies at different scales. The main performance metrics include recall, F1 value and area under the curve (AUC). The experiment showed that when the proportion of fraudulent users was 0.035, the recall value of reputation ranking technology strategy based on user evaluation mode and bias was 0.79, with stability exceeding 0.990. After applying the GNR metrics, the deviation ranking method showed a significant reduction in peak user count and improved the overall performance by 9.40%. The accuracy of the iterative group-based ranking and the iterative balance ranking increased by 2.89% and 2.54%, respectively. After introducing the adversarial data augmentation technology, the fraud detector based on graphical neural networks improved recall and F1 by 1.20% and 1.34%, respectively compared with the disguised fraudster model in the case of data scarcity. It can be seen that the method combining multiple strategies and technologies demonstrates improved performance in e-commerce user evaluation fraud detection, far surpassing traditional methods. This study has brought significant significance and value to the e-commerce field.

Povzetek: Predstavljena je kombinacija analize uporabniških ocen in grafnih nevronskih mrež (GNN) za identifikacijo zlonamernih e-trgovinskih uporabnikov. Predlagana metoda izboljšuje zaznavanje prevar ter povečuje zanesljivost modela z uporabo metrik GNR in tehnike nasprotnega učenja podatkov.

1 Introduction

With the vigorous development of e-commerce, user review has become a key decision-making factor for purchasing goods on e-commerce platforms. However, given the increasing number of fraudulent user comments, their impact on buyers and businesses is becoming increasingly significant, leading to distorted consumer decisions and loss of commercial benefits [1-3]. Therefore, accurately identifying forged user reviews and ensuring the integrity and health of the e-commerce environment are important issues that urgently need to be addressed in the current e-commerce field. The main research challenge is how to accurately distinguish between genuine and fraudulent evaluations, while also considering the concealment and variability of fraudulent behavior. This makes traditional methods often ineffective to a certain extent and unable to meet the needs for efficient and accurate identification of counterfeit evaluations [4-6]. Traditional rule-based methods are often difficult to handle large amounts of complex evaluation data. Machine learning methods also have certain limitations in dealing with data sparsity and cold start problems. Graph Neural Networks (GNN) is an emerging deep learning model, which can effectively learn features on graph structured data. Compared with traditional machine learning methods, GNN has shown significant advantages in handling complex user behavior patterns and large-scale data. By modeling users and their interaction behaviors in e-commerce platforms as graphs, GNN can better capture the relationships and behavior patterns between users, thereby improving the accuracy and robustness of malicious user identification. The main goal of this research is to address the problem of how to accurately identify fake user reviews among many genuine reviews. To this end, this paper proposes an integrated approach that combines a user rating mechanism with a Reputation Ranking Method (RRM) based on Rating Patterns and Rating Bias (RPRD), metrics, and adversarial data augmentation technology, aiming to improve the accuracy of identifying fake user ratings. The innovation of this study is to combine user rating behavior analysis with GNN to improve the robustness and accuracy of the model through adversarial data augmentation technology. The study introduces GNR metrics to improve the accuracy of identifying fraudulent user behaviors and adds adversarial data augmentation technology to gain insights into the

behavioral patterns of malicious users to improve the stability of identifying user behaviors. The overall structure of the study includes four sections. Firstly, the research achievements and shortcomings of neural networks and user ratings both domestically and internationally are summarized. Secondly, a reputation technology that combines user rating mechanisms with evaluation biases is introduced, along with GNR metrics and adversarial data augmentation technology. Then, related experiments are conducted to identify and analyze malicious e-commerce users based on user rating behavior and GNN. Finally, the experimental results are summarized, and the shortcomings and future research directions are proposed.

2 Related works

The scoring behavior of e-commerce users has become a research focus in recent years. With the widespread application of neural networks in data analysis, their value in user rating analysis is increasingly significant. Rating not only reveals consumer experience, but may also involve malicious behavior [7]. The following introduces some research on neural networks and user ratings. Wang *et al.* proposed a model based on neural networks-Cross domain Explicit Implicit Hybrid Neural Network (CEICFNet). This model combined deep neural networks to learn potential factors from explicit scoring and implicit interaction, thereby achieving cross domain learning. It included a domain shared multi-layer perception network that learned the potential factors of user and project ratings, serving as a knowledge transfer bridge. The experimental data proved that the model had better performance [8]. Guo *et al.* proposed a deep GNN social recommendation framework suitable for future applications of the Internet of Things. This method first converted the user and item feature space into two graph networks, and encoded them through a GNN strategy. Next, these two encoding spaces were nested into the potential factors of matrix decomposition to fill in the missing ratings in the user product rating matrix. The efficiency and stability of the model were verified through experiments on three real datasets [9]. Liu *et al.* proposed a hybrid neural recommendation model that extracted deep representations of users and items from ratings and comments. This model included a comment-based encoder to model users and items, as well as a prediction module to make recommendations based on ratings and comments. To fully utilize the information in comments, the study introduced a comment level attention mechanism to select key comments. The tests on multiple datasets showed that this model outperformed existing methods in recommendation tasks [10]. Da *et al.* combined fine-grained user item semantic information and used neural attention techniques to learn representation. The model learned heterogeneous user/item representations through comments and specific interactions. The model further integrated scoring-based features with comment specific features. A factor decomposition machine was applied to make predictions on a shared hidden layer. The experimental results showed that this method outperformed the baseline method in rating prediction and ranking [11].

Tang *et al.* proposed a neural joint model based on comments, product categories, and user co-purchase information. The comment module was responsible for learning user and product information, while the heterogeneous information network module extracted associated features from the heterogeneous information network. These data were subsequently fed into feature interaction methods for rating prediction. Testing on three datasets on Amazon showed that the model performed better than other baseline methods [12]. Wang *et al.* proposed a multi-attention deep neural network recommendation model that combined embedding and matrix decomposition, aiming to address data sparsity and cold start issues. The GPU-based deep network ensured the scalability of the model. Compared with traditional matrix decomposition methods, this model exhibited better prediction performance on real datasets, further improving the quality and performance of recommendations [13]. Shi *et al.* proposed an emotion enhanced neural graph recommendation method that integrated text comments and bipartite graph information. Through a hierarchical attention mechanism and emotional assistance tasks, users could identify their multifaceted preferences for items from comments. Graph convolutional networks were used to simulate information diffusion in user item interaction graphs, thereby capturing user interactions and preferences. Finally, the decomposition machine model was used to implement recommendations. The experiment on two datasets showed that the prediction accuracy of this model surpassed other related methods [14]. Liang *et al.* combined rating and topic level comment information into a deep neural framework. User preferences and item attributes in comments were captured through topic alignment operations and attention mechanisms. The neural prediction layer of this model extended user and item representations, integrating potential scoring factors and text information. The experimental results showed that this method surpassed the current state-of-the-art recommendation techniques in rating prediction, which could classify user/project comments by topic [15]. Li *et al.* proposed a GNN based on local and global perceptual memory (LGM-GNN) to optimize the fraud detection task. The network fused and utilized local and global information through relationship-aware embedding and interactive aggregation of local and global memory networks. The results showed that the LGM-GNN outperformed other methods on a real-world fraud detection dataset [16]. To improve the performance of GNN in e-commerce review fraud detection, and solve the sample class imbalance and fraud camouflage, Li *et al.* proposed a fraud detection method based on self-paced graph contrast learning (SPCL-GNN). The graph structure was first optimized by label equalization and self-paced graph contrast learning. Then the attention mechanism was introduced for node embedding. The results showed that SPCL-GNN outperformed the baseline method on Amazon and

YelpChi datasets [17]. To deal with gang fraud in e-commerce platforms, Yu *et al.* propose a novel end-to-end semi-supervised Group-based Fraud Detection Network (GFDN). The model supported real-world fraud detection by analyzing the characteristics of group fraud behavior. The results showed that the GFDN exhibited better effectiveness and efficiency in group fraud detection on bi-directional graphs on Taobao and Bitcoin datasets [18].

In summary, many scholars have conducted in-depth research on user ratings and recommendation accuracy, and have successfully applied them in multiple fields. However, there is still relatively little comprehensive research on e-commerce user ratings and GNN e-commerce malicious user identification. Therefore, this study proposes a new solution strategy for e-commerce user rating and recognition. The study first introduces a reputation strategy based on user rating mechanism and evaluation bias. Then the reputation calculation method is enhanced by combining GNR metrics. Finally, the Free Large-scale Adversarial Augmentation on Graphs (FLAG) technology further strengthens the deception recognition model. This comprehensive model provides an efficient and reasonable new solution for user rating and recognition in the e-commerce field, which is of great significance for the development of this field.

Table 1 Different literature and research methodology gaps

Literatures	Research purpose	Results and gaps
Wang et al. [8]	CEICFNet	Can learn potential factors, but cannot achieve user fraud identification and analysis
Guo et al. [9]	Deep GNN Social Recommendation Framework	Able to fill in the potential factors of user coding, but under-applied for user fraud identification and correlation analysis
Liu et al. [10]	Hybrid Neural Recommendation Model	Capable of user rating and recommendation, not able to refine the user fraud identification process
Da et al. [11]	Neural attention techniques	Capable of integrating user rating features but unable to apply user fraud prediction
Tang et al. [12]	Neural Joint Model	Capable of user data interaction, but poor for user behavior recognition
Wang et al. [13]	Multi-attention deep neural network recommendation model	With good matrix decomposition ability, but cannot perfectly guarantee the predictive analysis of user fraudulent behavior
Shi et al. [14]	Sentiment-enhanced neural graph recommendation method	User comment recognition can be achieved, but the effect on user behavior recognition still needs to be improved
Liang et al. [15]	Deep Neural Networks	Able to recommend users based on topics does not build a more effective user behavior system
Li et al. [16]	LGM-GNN	Can combine global information, but the model performance is poor
Li et al. [17]	SPCL-GNN	Able to improve user fraud problem camouflage, but the method is more complicated to use
Yu et al. [18]	GFDN	Can analyze team fraud behavior, but cannot identify individual behavior

3 E-commerce malicious user identification method construction based on user rating behavior and GNN

This study focuses on the e-commerce user rating and recognition. Firstly, a reputation strategy based on user rating mechanism and evaluation bias is proposed. Subsequently, a GNR-based indicator is provided to enhance reputation calculation methods. Finally, the FLAG technology is used to enhance the deception recognition model.

3.1 Reputation model construction based on user rating mechanism and evaluation bias

Malicious users are becoming increasingly apparent on online e-commerce trading platforms. According to user rating behavior, these actors often have a clear purpose. To distinguish these consumers, an evaluation mechanism is designed. Consumers with high evaluation values are considered trustworthy, while low evaluation values may belong to negative actors. This study introduces raking habits and tendencies to identify these users. To ensure the authenticity of the data, the study uses a ternary model to improve computational efficiency, expressed as (i, j, r), where i represents consumers, j represents items, and r represents the corresponding raking. Based on the rating trend, the evaluation values are calculated and the classification strategy is optimized. The specific strategy is that most ratings should reflect the actual value of the project and follow a normal distribution [19-20]. The probability distribution of each participant is shown in equation (1).

$$g_i(q_a^{abs}) = N(f_i(O_a), \sigma_i^2) \quad (1)$$

In equation (1), μ and σ respectively represent the mean and difference. q_a^{abs} represents the absolute value of the identification item a. O_a represents the a -numbered item. $f_i(\cdot)$ is the i consumer's identification method. Due to the difficulty in knowing the true value of items in actual situations, this study replaces their true value with the average number of evaluations obtained from each item. The actual value of each item is shown in equation (2).

$$q_a^{avg} \equiv \frac{1}{|U_a|}\sum_{i \in U_a} b_{ia} \quad (2)$$

In equation (2), $|U_a|$ represents the number of users who rate the item a. $|U_a|$ represents the rating of consumer i to item a. If the evaluation scores of the item O_a are sufficiently concentrated, the average value q_a^{avg} of the item should be close to its intrinsic value q_a^{abs}. Therefore, equation (1) can be optimized, as shown in equation (3).

$$g_i(q_a^{avg}) = N(b_{ia}, \sigma_i^2) \quad (3)$$

In equation (3), σ_i^2 refers to the variation coefficient of consumer users i. Due to differences between consumer feedback and the actual value of the item, the deviation degree of each consumer identification method needs to be calculated in the future. The threshold ranges in equations (1)-(3) are determined by analyzing the distribution of user ratings and identifying the points where the behavior of malicious users deviates significantly from that of real users. It can be adjusted according to the standard deviation of user ratings. The average price of an item follows a normal model within a subset O_{is}. Therefore, the probability model for consumer rating is shown in equation (4).

$$g_i(q_{is}) = N(s, \frac{\sigma_i^2}{|O_{is}|}) \quad (4)$$

In equation (4), $q_{is} = (1/|O_{is}|)$ represents the evaluation quality of consumers i providing s level evaluation. $|O_{is}|$ represents the number of s level items provided by the user i. This study uses Z value to measure the reliability of evaluations submitted by consumers, as shown in equation (5).

$$Z_{is} = \frac{\sqrt{|O_{is}|}(q_{is} - s)}{\sigma_i} \quad (5)$$

In equation (5), σ_i represents the deviation of consumers i. The previous steps are further integrated to assign evaluation credibility values r_i to each consumer. In the construction stage of this method, the Z value of the s level proposed by consumers i is negatively correlated with their evaluation reputation. Therefore, the evaluation reputation method for each consumer should be the $|Z_{is}|$ descent method. To integrate each $|Z_{is}|$ into a reputation value r_i, it is calculated from equation (6).

$$r_i = -\frac{\sigma_i \sum_{S=1}^{L} |Z_{is}|}{\sqrt{|O_i|}} = -\frac{\sum_{S=1}^{L} \sqrt{|O_{is}|}\,|q_{is} - S|}{\sqrt{|O_i|}} \quad (6)$$

In equation (6), L represents the maximum rating limit for consumers. Z_{is} is the adjusted Z value of consumer i rating level. On this basis, the motivations, rating trends, and biases of malicious consumer users are further analyzed. To improve the accuracy of rating reputation values, this study introduces the information entropy index and likelihood difference based on the rating reputation value. The former is used to describe the rating trend, and the later is used to describe the scoring bias. The information entropy index of each consumer user is displayed equation (7).

$$g_i = (-1)^k \sum_{s=1}^{L} p(t_{is}) \log_e p(t_{is}) \quad (7)$$

In equation (7), k represents the measurement of user attributes. $k = 1$ represents the identification of random malicious users, and $k = -1$ represents extreme malicious users. To correct the scoring bias, probability analysis is used in the study. h_i represents the probability shift of each consumer user, as shown in equation (8).

$$h_1 = \frac{1}{2}\sum_{S=1}^{L-1} \sqrt[3]{|p(t_{i(s+1)}) - p(t_{is})|} \quad (8)$$

In summary, this study elaborates on the reputation technology process based on user rating mechanism and evaluation bias through examples. Figure. 1 shows the bipartite network composed of users and products, involving 18 evaluations. This includes the user product rating table, the average matrix of the product, the user rating matrix, the user information entropy and probability difference, and the final reputation matrix of the user.

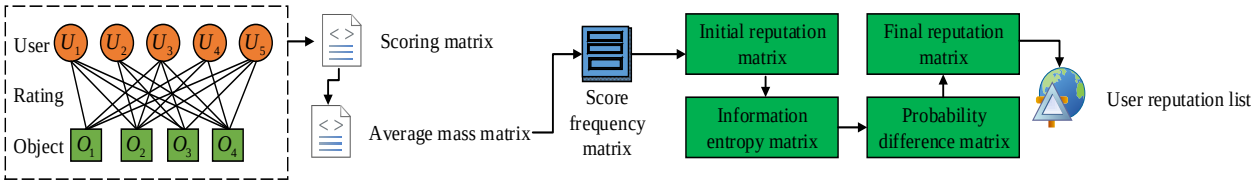


Figure 1: A two-part network diagram of the user and the product

3.2 GNR index for reputation ranking based on evaluation preference and bias

On the basis of reputation ranking based on user evaluation preferences and biases, a comprehensive framework is proposed to improve the current ranking method. This framework not only improves the efficiency of existing technologies, but also reduces the development time and cost. Due to the frequent attacks of malicious users on online rating systems, such as extremely malicious users employed by merchants or randomly rated malicious users, this affects the credibility of the system. There is a significant difference in the rating behavior between normal users and malicious users. Normal users are distributed in a hierarchical manner, while malicious user rating patterns are not. In addition, the study introduces Gini coefficient and range as indicators to measure the distribution differences of ratings, which are combined into GNR metrics, as shown in Figure. 2.

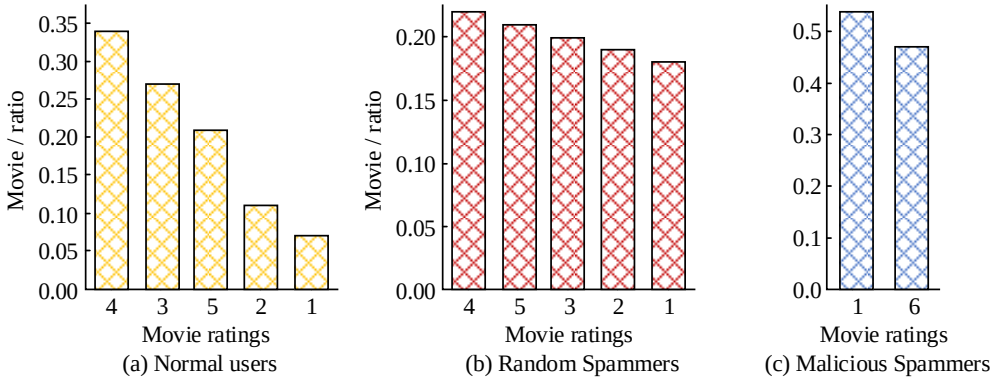


Figure 2: User ratings of GNR metrics

The GNR comprehensive standard is derived from the past evaluations of consumer users, calculated through Gini parameters and extreme differences. According to equation (9), it is possible to standardize the interval between two ratings for a specified user.

$$G_i = \theta\left(\frac{1}{2 * t_i^2 * r_i^{avg}}\right)\sum_{a=1}^{a=t_i}\sum_{\beta=1}^{\beta=t_i}(r_{ia} - r_{i\beta}) \quad (9)$$

In equation (9), r_i^{avg} represents the median of evaluations assigned to each user. t_i represents the frequency of all evaluations by user j. r_{ia} represents the evaluation of user i to item a. The Gini coefficient and range introduced in equation (9) are used to measure differences in rating distribution. This is to capture the inequality in rating distribution and identify users who rate projects in an abnormally biased manner. The extreme difference of each user is shown in equation (10).

$$Range_i = \frac{t_{i\beta}^{\max} - t_{i\beta}^{\min}}{t_{i\beta}^{\max} + t_{i\beta}^{\min}} \quad (10)$$

In equation (10), $t_{i\beta}^{\max}$ represents the highest evaluation frequency of the user x's β class. $t_{i\beta}^{\min}$ represents the lowest evaluation frequency of the user i in the β class. The Deviation-based Ranking (DR) algorithm reveals the reliability of users through user evaluation patterns. This is essentially a difference-based arrangement technique, where user statistical data is defined by scores. This strategy divides each user's credit based on their accuracy in project evaluation [21]. Combining the GNR standard with the DR strategy, this method mainly derives from the fact that most users' evaluations of a certain product are closely related to the actual quality of the product, as shown in equation (11).

$$g_i(q_a^{abs}) = N(f_i(o_a), \sigma_i^2) \quad (11)$$

In equation (11), μ represents the mean and σ refers to the variance. This study illustrates the process of GNR metrics in DR strategy through examples, as shown in Figure. 3. Initially, it is a bidirectional graph network composed of items and users, covering 18 ratings. Subsequently, it is a rating table for users and items, followed by an average quality table. Next is the

Gini value and extreme value matrix for users, followed by a GNR matrix. Finally, the user's reputation ranking table is displayed.

The Iterative Group-based Ranking (IGR) algorithm introduces iterative thinking on the basis of the grouping sorting algorithm to redistribute user reputation. This strategy is that in a large group, user ratings with high credibility are more persuasive. The application of GNR algorithm in IGR is shown in Figure. 4. The beginning is a two-way diagram constructed by the item and the user. Subsequently, there is a user rating table for the item, followed by a weight restructuring table and a rating reward table. Next is the user Gini value and extreme value table, followed by the user GNR table, user first iteration reputation, and final reputation ranking.

The Iterative Balance Ranking (IBR) algorithm is a high-quality reputation ranking method that should reduce bias in user ratings. This law aims to fairly evaluate the reputation of each user and reveal the true performance of the product. The application of GNR metrics in IBR is shown in Figure. 5.

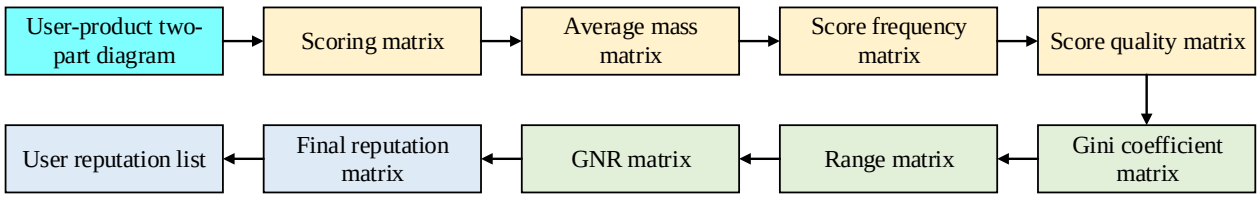


Figure 3: GNR metrics flow in the DR policy

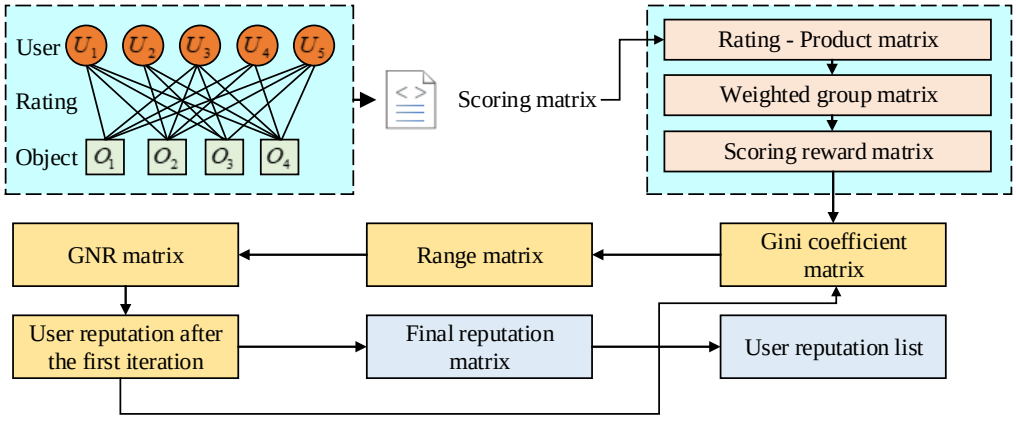


Figure 4: Flow chart of GNR metrics in IGR algorithm

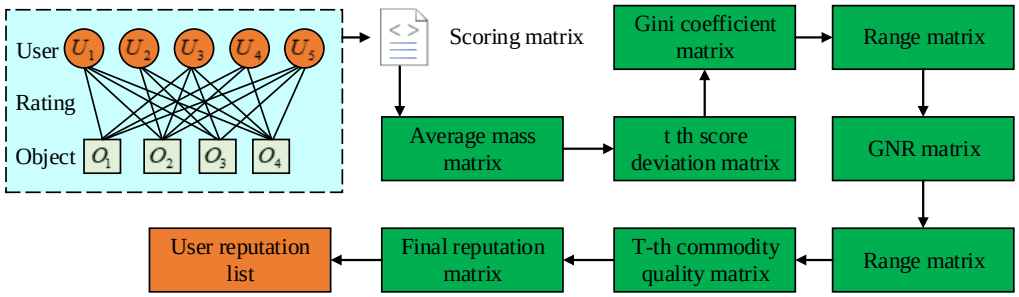


Figure 5: Flow chart of GNR metrics in IGR algorithm

3.3 GNN-based method for identifying malicious e-commerce users

To improve the efficiency of fraud detection, this study introduces the FLAG method and the Graph Convolutional Neural Network (C-GNN) model, which is a GNN-based fraud detectors against camouflaged fraudsters. GNN can effectively capture the complex interaction between users and projects, and identify patterns hidden in the graph structure. After introducing the FLAG method in GNN, GNN can enhance its robustness to malicious data disturbances, and improve the accuracy and stability of the model in fraud detection. GNN can also extract deep features of nodes layer by layer through multi-layer convolution operations, improving the recognition ability of fraudulent behavior. Finally, GNN can evaluate the performance stability of models in large-scale data and malicious user attacks. Therefore, GNN is used as the main structure of the study. The C-GNN can effectively process graph structured data and capture complex relationships between users and projects. The nodes in the graph

network represent users and items, and the weights of edges represent ratings. Through multi-layer graph convolution operation, the information of node neighbors is aggregated layer by layer to learn the representation of nodes. In graph convolution, attention mechanism is introduced to focus on neighboring nodes with strong correlation with the target node. Finally, after introducing the FLAG method, the robustness of the model is enhanced by gradient perturbation of node attributes. GNN can combine Gini coefficient and range as evaluation criteria to optimize the ranking method of user rating preferences and biases, which can significantly improve the performance of existing methods. In the initial GNN, IGR and IBR algorithms are used to iteratively adjust user reputation, reduce rating bias, and improve fairness and accuracy of ratings. Finally, adding FLAG technology to generate adversarial samples can enhance the model generalization ability and performance in data scarcity situations. Under this strategy, a fraud detection network is established and trained. Furthermore, through data augmentation, false nodes and real nodes are generated and mixed. During testing, real nodes are used to predict classification. Model evaluation shows that the FLAG method significantly improves the accuracy of fraud detection. Equation (12) shows the calculation details. In the digital age, it is particularly important to establish the efficient fraud detection model.

$$D^{(l)}(v,u) = \left\| \sigma(MLP^{(l)}(h_v^{(l-1)})) - (MLP^{(l)}(h_u^{(l-1)})) \right\|_1 \quad (12)$$

In equation (12), $D^{(l)}(v,u)$ shows the l_1 interval between core point v and its adjacent point $u \in N(v)$ at the l level. In C-GNN, the similarity measurement between points is shown in equation (13).

$$s^{(l)}(v,u) = 1 - D^{(l)}(v,u) \quad (13)$$

C-GNN evaluates the matching degree between nodes separately at each layer. After the matching evaluation is completed, attention should be paid to nodes with strong correlation. However, as the training continues, the data of the nodes may change. To address this problem, C-GNN integrates the reinforcement learning part and dynamically adjusts the node aggregation degree in each context, which is expressed as $p_r^{(l)} \in [0,1]$. In a specific connected environment, the model uses the primary sampling method to aggregate nodes. If the total distance between nodes in a certain connection decrease, it indicates that the center and adjacent nodes are increasingly matching. At this point, the $p_r^{(l)}$ value should be increased to collect more data, in order to more accurately determine the type of center node [22-23]. This model utilizes the integration of various connections to refresh the embedding of the central node. There are two main steps. The first step is to perform internal integration on the central node within each connection, as shown in equation (14).

$$h_{v,r}^{(l)} = AGG_r^{(l)}(\{h_u^{(l-1)}, u \in N(v), e_{u,v} \in E_r\}) \quad (14)$$

In equation (14), the embedding vector of v is $h_{v,r}^{(l)}$ under the l -layer relationship r. After completing this step, there is a series of embedding vectors. Then, the further integration is carried out based on the weight $p_r^{(l)}$, as shown in equation (15).

$$h_{v,r}^{(l)} = \sigma(h_v^{(l-1)} + AGG^{(l)}(\{p_r^{(l)}, h_{v,r}^{(l)}\}|_{r=1}^{R})) \quad (15)$$

In equation (15), $h_{v,r}^{(l)}$ is the central node update vector passing through layer L. The FLAG strategy increases the stability and accuracy of the model by injecting gradient-based perturbations into node attributes. This involves creating aggressive data points and incorporating them for training, as shown in equation (16).

$$\min E_{(x,y)\sim D}\left[\max_{\|\delta\| p \le \epsilon} L(f_\theta(x+\delta), y)\right] \quad (16)$$

In equation (16), D represents the dispersion of node data, X is the node attribute, and Y is the node label. L is the solving objective. δ is the generated perturbation group. $\|\cdot\|_p$ represents distance measurement of l_p. Equation (16) introduces parameters that control the injected node attribute perturbations. This parameter selection balances the weight between enhancing the model's generalization ability and maintaining the stability of the training process. This problem requires searching for aggressive sample sets to maximize internal losses, while minimizing the losses of the model on this sample set. The projection gradient descent is used to limit the l_p specification, as shown in equation (17).

$$\delta_{t+1} = \prod_{\|\delta\|_{p\le\epsilon}} (\delta_t + a \cdot sign(\nabla_\delta L(f_\theta(x+\delta_t), y))) \quad (17)$$

In equation (17), the projection gradient descent strategy uses continuous iterations, which generate aggressive interference $\delta_{1:M}$ after M rounds of iterations. Figure. 6 shows the general process of this method in node classification. Finally, the sample set and its aggressive interference are integrated into C-GNN as the entry node.

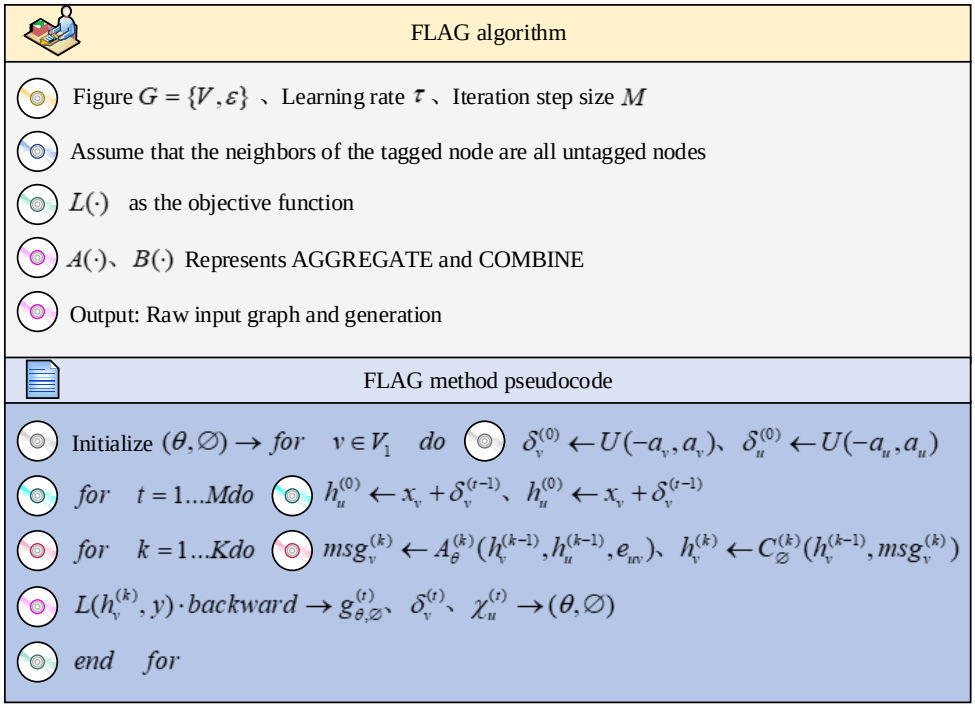


Figure 6: FLAG pseudo-code of the algorithm

4 Malicious e-commerce users' identification and analysis based on user rating behavior and GNN

This experiment first compares the effectiveness and robustness of user recognition among three sample sets. Next, to test the enhancing effect of GNR metrics in reputation ranking technology, F1 and Recall of four algorithms are compared. Finally, the designed method is validated on the fraud detection model of C-GNN. The results show that the model improves the accuracy and robustness.

4.1 Comparative analysis of user identification effectiveness and robustness using adversarial data augmentation

This research experiment used three sample sets, namely Netflix, Movielens2, and Movielens_100, mainly recording users' ratings of movies. The Netflix dataset contains user ratings of movies on a 10-point scale. The Movielens2 dataset contains a 5-point rating system for movies by users. The Movielens_100 dataset contains a 5-point rating of movies by users. The preprocessing process of the model first collects the user rating data for movies from these three datasets (Netflix, Movielens2, Movielens_100) by removing outliers and missing values. Then, the users and items are used as nodes and ratings are used as weights of edges to extract features from user rating behavior. The GNN model consists of 2-5 graph convolutional layers. The hidden units of each layer are set according to the model complexity and the size of the dataset. The activation function is ReLU. The study selects recall rate, F1 value, and Area Under Curve (AUC) as the measurement indicators for the model. The recall can measure the proportion of actual fraudulent users identified by the model. The F1 value can comprehensively consider the accuracy and recall of the model as a comprehensive evaluation indicator. AUC can quantify the classification performance of a model under different thresholds. The Netflix used a 10-point scale, while the other two used a 5-point scale. This study first identified 50 malicious users, and then changed the L value to calculate the recall rates of different strategies to evaluate accuracy. The ideal fraud detection method should accurately identify malicious users in most scenarios and maintain high accuracy even when data is scarce. This experiment examines the performance of four strategies, RPRD, DR, IGR, and IBR, on three databases, as shown in Figure. 7. In Figure. 7, L represents the number of selected users. Different sub-graphs represent different recall rates for malicious user detection.

In the first three sub-graphs, RPRD and IBR performed better in identifying extremely malicious users. In the last three sub-graphs, RPRD was significantly ahead in detecting random malicious users. Especially in sub-graph 7 (e), RPRD outperformed DR, IGR, and IBR even in the context of big data. Preliminary experiments showed that RPRD was particularly effective in identifying small-scale malicious users, especially for random malicious users. Further experiments observe the changes in recall rates of malicious users in different methods, as shown in Figure. 8.

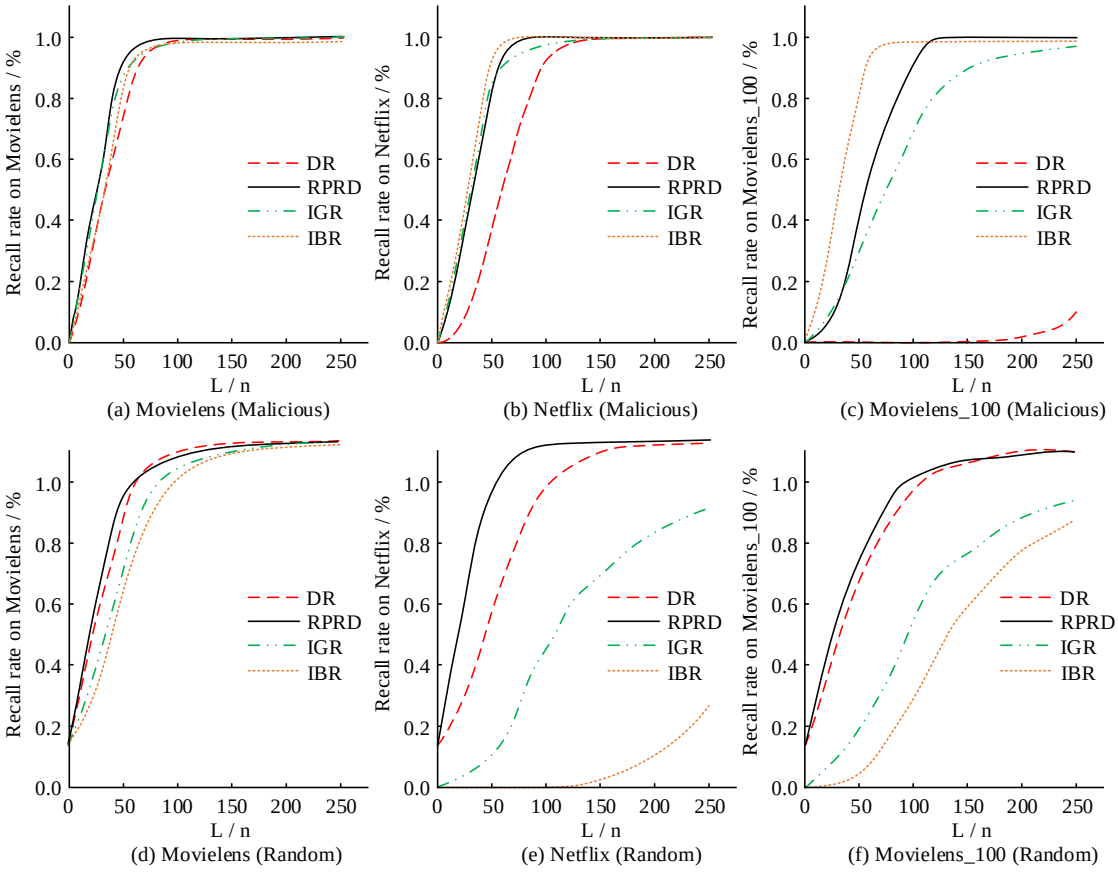


Figure 7: Comparison effect of user recognition

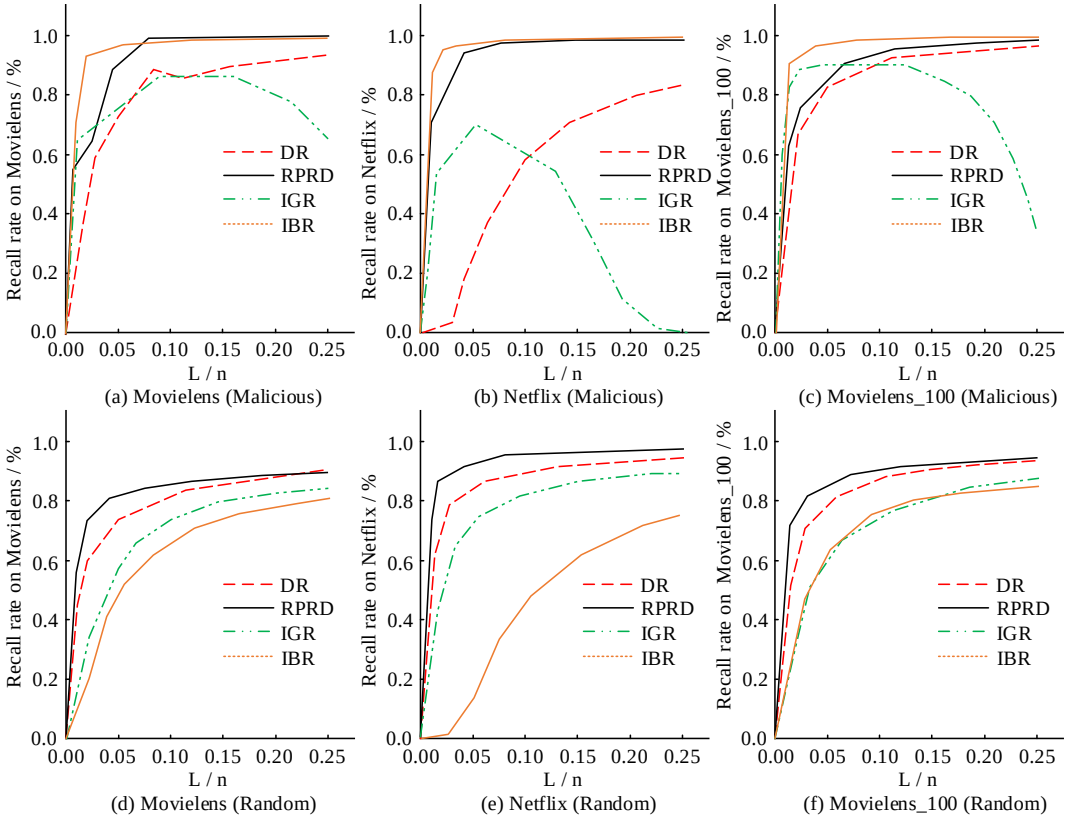


Figure 8: Variation of recall rate by different methods

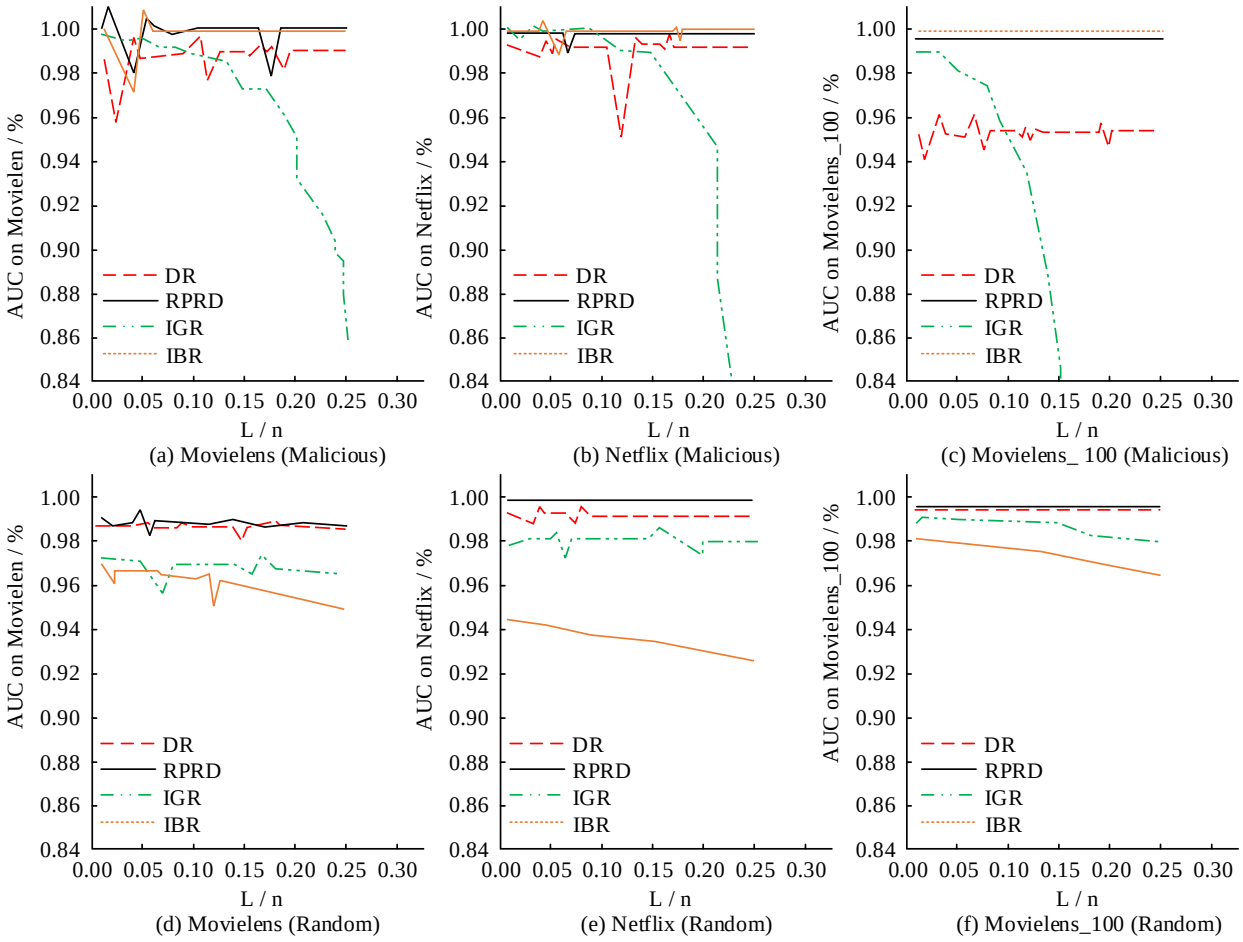


Figure 9: Comparative robustness of user recognition

In the three sub-graphs (a-c) of Figure. 8, RPRD and several other methods showed good results in detecting malicious users. Especially, when the proportion of fraudulent users was 0.035, RPRD and IBR performed well, with a recall value of 0.79. However, after the proportion of malicious users increased, the performance of the IGR method began to decline, reaching only 0.89, indicating that it may have shortcomings in large-scale malicious user attacks. This indicates that introducing RPRD strategy can effectively distinguish between real users and malicious users. Detecting malicious users is effective, especially when the proportion of malicious users is very small. For random malicious users, RPRD always led in the last three sub-graphs (d-f) of Figure. 7, which had significant advantages over DR, IBR, and IGR, especially in identifying random malicious users. RPRD used specific algorithmic equations to distinguish user rating patterns, avoiding algorithmic issues when there were a large number of malicious users. Next, the robustness analysis of each method is conducted, as shown in Figure. 9.

From Figure. 9, as malicious users increased, RPRD remained at 0.98 to 1, significantly leading other models. Even when dealing with millions of ratings, the AUC was still maintained above 0.990, showing strong stability. After incorporating information entropy and probability difference, RPRD effectively reflected the difference in ratings between normal and malicious users, surpassing DR, IGR, and IBR, especially in identifying random malicious users. The core concept of this method is based on fundamental assumptions, utilizing specific equation characteristics to ensure the accuracy of user classification and avoid algorithm failure caused by a large number of malicious users. RPRD also efficiently utilized a triplet structure to store data, improving operational and spatial efficiency. It has been proven that RPRD exhibits better stability and robustness, which can effectively resist malicious user attacks.

4.2 Comparative analysis of the performance of GNR metrics model using adversarial data augmentation

This study tests the complementary ability of GNR metrics to reputation ranking techniques. The study uses a fixed number of 50 malicious users to observe the changes in recall rate. Each experiment is independently repeated 100 times. The comparative effect based on the GNR metrics is shown in Figure. 10.

In Figure. 10, the accuracy of the DR, IGR, and IBR methods in identifying malicious users improved after applying GNR metrics. Specifically, the peak user count of DR method on Movielens and Netflix data decreased from 95-100 to 55-60. Especially in

Movielens_100, the accuracy increased from 0.07 to 0.88, resulting in an overall performance improvement of 9.40%. Although IGR and IBR already had strong detection capabilities, they also slightly improved after applying GNR, with the accuracy increasing by 2.89% and 2.54%, respectively. These indicate that the GNR significantly enhances the ability to measure score distribution differences and identify malicious users. The last three sub-graphs (d-f) of Figure. 10 showed that the efficiency of these three methods in identifying random malicious users increased by 5.52%, 17.12%, and 32.24%, respectively, proving that GNR enhanced the accuracy of these methods. The next step is to conduct a comparative robustness analysis based on the GNR, as shown in Figure. 11.

In Figure. 11, after applying the GNR universal indicators, the baseline method was enhanced in detecting both extreme and random malicious users, especially the IGR and DR methods. The IGR method also solved the problem caused by the increase in fraudulent users. It can be proven that these enhanced methods still maintain higher robustness and accuracy in a large number of malicious attacks.

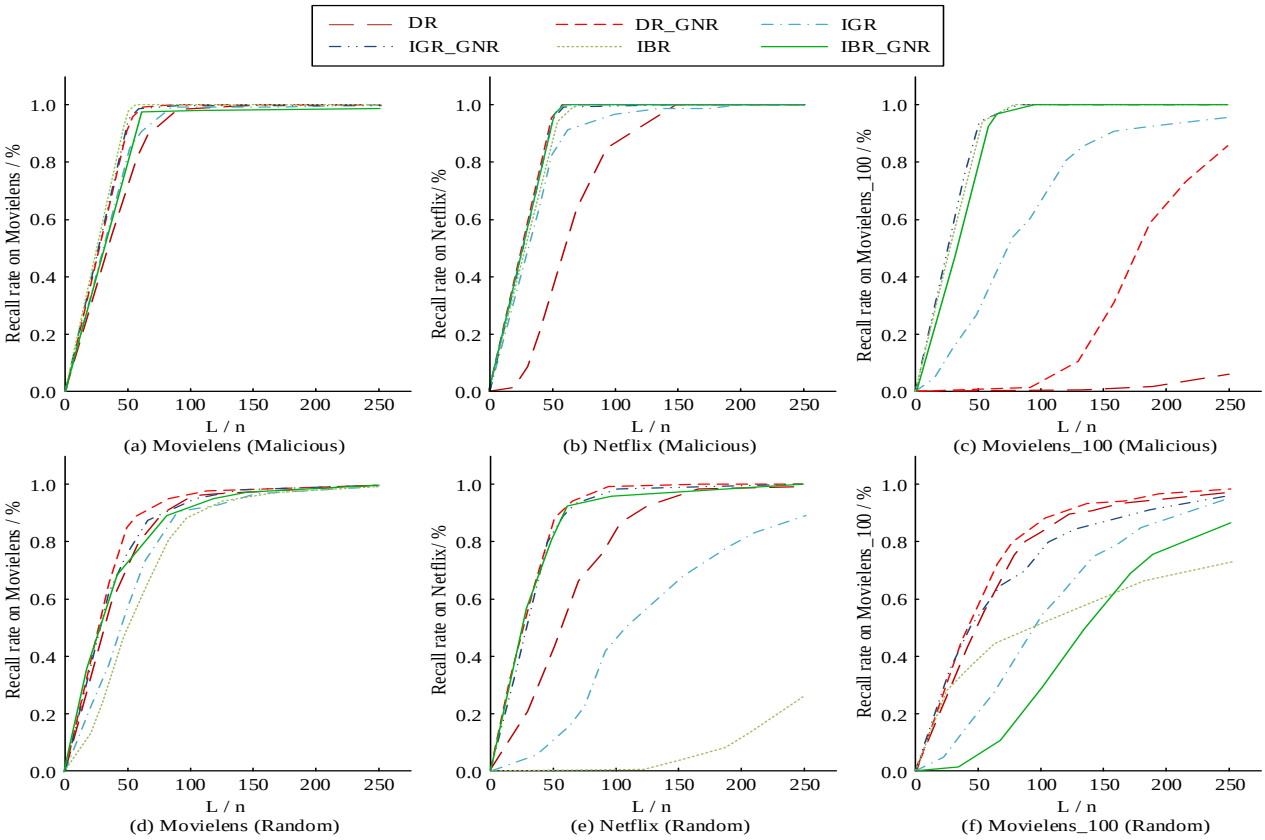


Figure 10: Comparison effect based on GNR

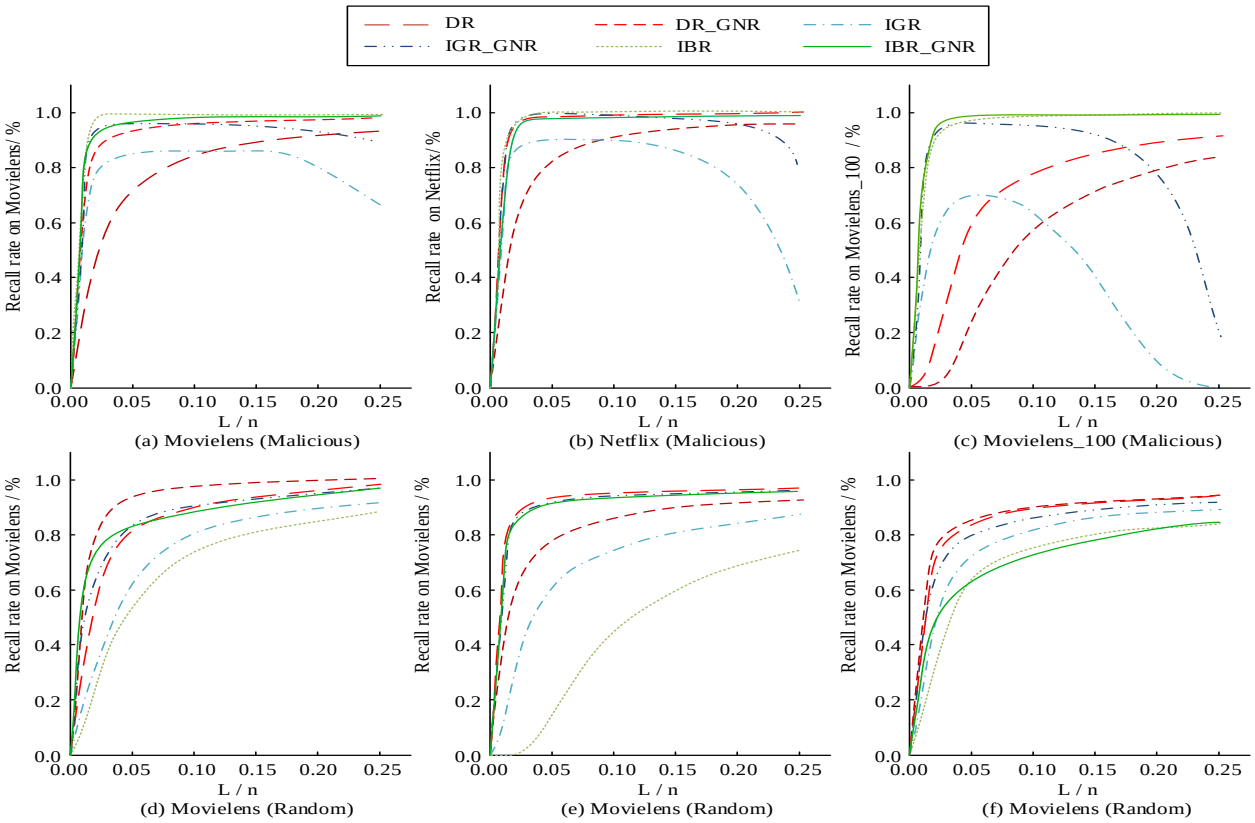


Figure 11: Comparative robustness analysis based on GNR index model

4.3 Comparative performance analysis of C-GNN fraud detection models augmented with adversarial data

This study introduces the FLAG method to the C-GNN model on the C-Yelp and C-Amazon datasets to observe changes in accuracy. In Figure. 12, the accuracy of C-GNN significantly improved using the FLAG method, especially when the training data was limited. For example, when the training set was 5%, the recall and F1 improved by 1.20% and 1.34%. When the training set was 30%, the improvement was relatively small. When the training data increased to 40%, the accuracy improved significantly again. This proves that the FLAG method effectively enhances the performance of the C-GNN model.

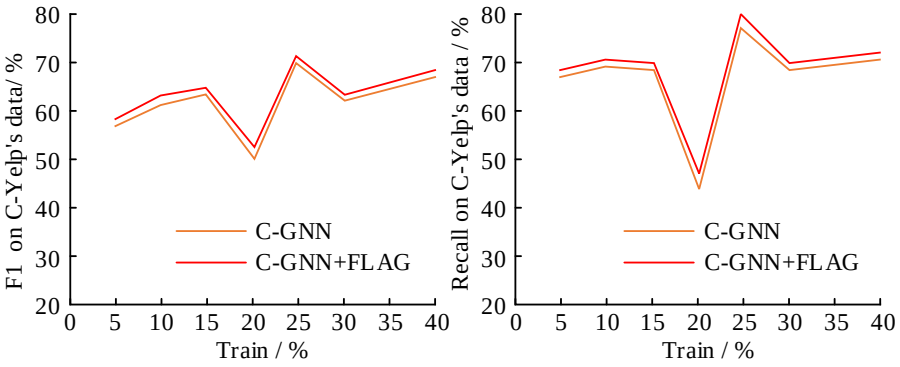
To further explore the improvement of the FLAG method on the C-GNN model, this study specifically introduces the AUC to quantitatively describe how the accuracy of the model changes under different training conditions. The detailed experimental results are shown in Figure. 13. When the FLAG method was applied to the C-GNN, the AUC significantly increased. Especially on the C-Yelp dataset and C-Amazon dataset, the growth range of the ACU was 0.06%-1.54% and 0.19%-1.14%, respectively. This indicates the effectiveness of the FLAG method in improving model performance and robustness. These data clearly demonstrate that the FLAG method effectively enhances the model's classification ability and improves its accuracy in detecting fraudulent users.

As shown in Table 2, the standard deviation and confidence interval of different methods tested on different datasets are analyzed.

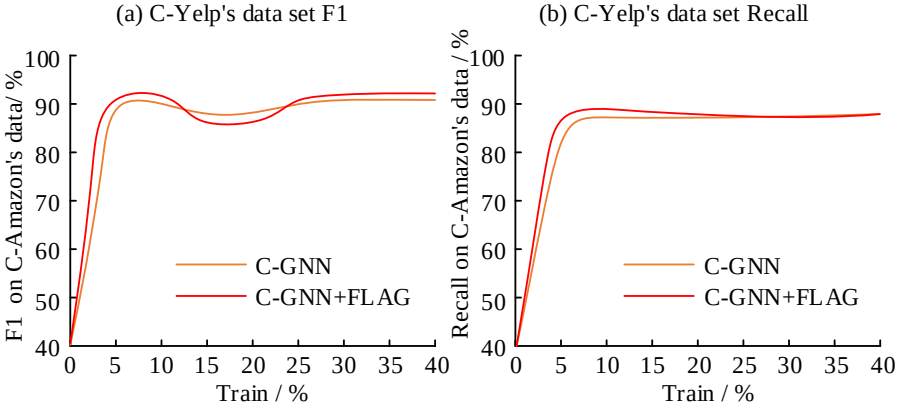
In Table 2, the confidence intervals for comparing different datasets and methods used for research are 95% or higher. The standard deviation used is between 0.01-0.02.

To compare the effectiveness of different methods for identifying malicious fraudulent behavior among e-commerce users, ML algorithm, behavioral biometric identification, and Multi-factor Authentication method (MFA) are compared with existing methods. The recognition performance of the algorithm is obtained using the dataset Movielens2, as shown in Table 3.

From Table 3, among the four methods, the research method achieved the highest recall rate of 91.2% in the Movielens2 dataset. Compared with the lowest ML algorithm, its recall rate increased by 3.6%. At the same time, the F1 and AUC values of the model showed good performance, with the F1 value increasing by 3.8% compared with the ML algorithm. The AUC value increased by 3.2% compared with the ML algorithm. When comparing the accuracy and specificity of different models, this study uses more accurate and specific methods, and processed each segment with better processing speed. The improved GNN model has better data processing performance and the ability to identify malicious fraudulent behavior of e-commerce users.

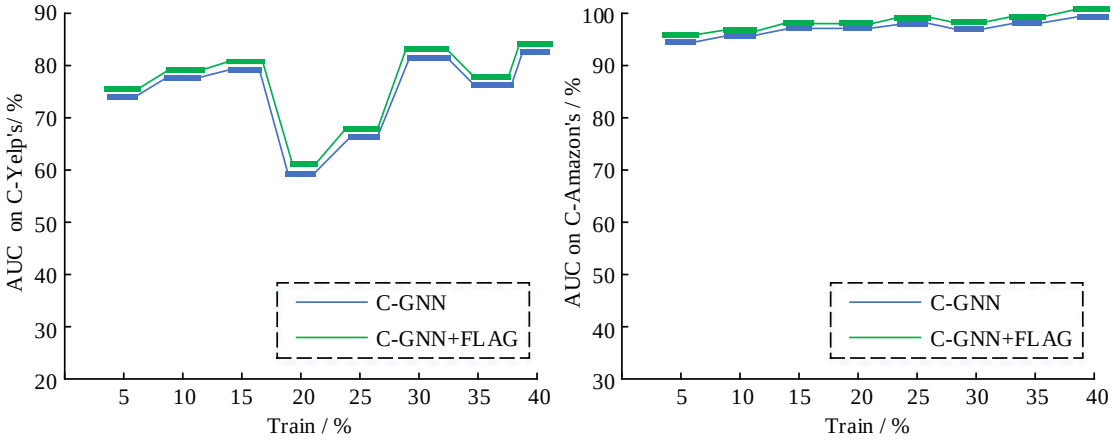


(a) C-Yelp's data set F1 (b) C-Yelp's data set Recall



(a) C-Amazon's data set F1 (d) C-Amazon's data set Recall

Figure 12: Comparison F1 and Recall of C-GNN model before and after FLAG method



(a) C-Yelp's AUC comparison (b) C-Amazon's AUC comparison

Figure 13: AUC of C-GNN model before and after FLAG method

Table 2: Confidence level and standard deviation of different methods under different data sets

Dataset	Method	Recall (%)	F1 (%)	AUC	Confidence Interval (95%)	Standard Deviation
Netflix	RPRD	0.79	0.85	0.96	(0.78,0.80)	0.01
	DR	0.75	0.81	0.94	(0.74,0.76)	0.02
	IGR	0.77	0.83	0.95	(0.76,0.78)	0.01
	IBR	0.76	0.82	0.95	(0.75,0.77)	0.02
Movielens2	RPRD	0.81	0.87	0.97	(0.80,0.82)	0.01
	DR	0.78	0.84	0.96	(0.77,0.79)	0.02
	IGR	0.8	0.86	0.97	(0.79,0.81)	0.01
	IBR	0.79	0.85	0.96	(0.78,0.80)	0.02

Movielens_100	RPRD	0.82	0.88	0.98	(0.81,0.83)	0.01
	DR	0.79	0.85	0.97	(0.78,0.80)	0.02
	IGR	0.81	0.87	0.98	(0.80,0.82)	0.01
	IBR	0.8	0.86	0.97	(0.79,0.81)	0.02

Table 3: Comparison of recognition performance of different methods

Method	Recall (%)	F1 (%)	AUC	Accuracy (%)	Idiosyncrasy (%)	Number of graph nodes processed per second(nps)
ML	87.6	88.6	92.4	86.8	83.4	68
Behavioral biometric recognition	89.5	89.7	93.5	89.4	84.6	73
MFA	88.4	90.3	92.1	91.3	92.4	83
Improved GNN	91.2	92.4	95.6	94.8	95.6	103

5 Discussion

The study compares the model used with the current state-of-the-art methods. The current research uses a method that combines user rating behavior analysis with graphical neural networks and adversarial data augmentation to better identify user fraudulent behavior. For example, the recall of the current method was 0.79 at 0.035. This indicates that the method has good performance, possibly because it can analyze user rating behavior in more detail and includes the GNN framework. Meanwhile, the stability of the research method in model comparison can exceeded 0.990. This indicates that the research method also has model stability and good reliability when dealing with large amounts of malicious user data. After adding graphical neural network to the model, the peak number of users in the model was significantly reduced and the overall performance was improved by 9.40%. User interactions and ratings can be effectively captured by adding GNNR, but the traditional SOTA method cannot capture the details of user interaction ratings. This study integrates adversarial data augmentation technology. In the entire study using this model, the accuracy of the IGR and the IBR improved by 2.89% and 2.54%, respectively. This indicates the need to enhance the application of the model by integrating the data network during model training and enhancement.

When comparing the research method with other advanced methods such as machine learning algorithms, behavioral biometrics and multi-factor authentication algorithms, the recall of the research method in the Movielens2 dataset reached a maximum of 91.2%, which was 3.6% higher than that of the machine learning algorithm. The F1 value and the AUC were also 3.8% and 3.2% higher than that of the ML algorithm, respectively. This may be due to the inclusion of an authentication module in the research method.

Although the currently used method has better application performance, there are still some drawbacks in the research method. For example, in some complex and diverse fraudulent behaviors, the performance of the research method may decrease, which may be due to the limitations of GNN in capturing subtle data changes in complex environments. For this reason, more complex environments will be explored in subsequent studies, while continuously improving the performance of the model to cope with complex environments to adapt to more diverse and changing fraud strategies. Meanwhile, the computational efficiency of the method used in the study still needs to be improved, and the model performance is also enhanced by reducing the computational complexity of the model in subsequent studies.

For extreme malicious users, adversarial data augmentation technology can improve the model's recognition accuracy by simulating user fraudulent behavior and helping the model learn how to recognize and defend against these extreme malicious behaviors. In the case of data scarcity, adversarial data augmentation enhances the generalization ability of the model by generating adversarial samples to simulate malicious user behavior. Faced with large-scale malicious user attacks, adversarial data augmentation improves the stability and accuracy of the model by continuously introducing perturbations during the training process, so that the model can adapt to and recognize malicious behaviors in large-scale attacks. Adversarial data augmentation can also help the model adapt to complex and changing fraud strategies, and improve its ability to recognize emerging fraudulent behaviors by learning more malicious behavior patterns. When the graph layers of the convolutional network are large, the computational complexity of the whole model is elevated. During the model training process, adversarial samples are incorporated into the model training, which leads to an increase in the computational complexity of the model. Secondly, as the model dataset increases, the size and complexity of the graph also increase, resulting in a significant increase in training and inference time for GNN models. In the given experiment, the training time of the model was not explicitly given, but it can be expected that as the size of the dataset increases, the training time will significantly increase. Therefore, to reduce the complexity of the

model in subsequent research, it is possible to train the model by reducing the dataset used and using lightweight models.

GNN-based methods have better advantages in handling complex relationships, large-scale data, robustness, and feature learning. This includes better model performance and data processing capabilities, such as higher performance testing of model accuracy, F1 score, and specificity, which makes GNN based methods superior to non-GNN-based techniques. These advantages make GNN particularly suitable for malicious user identification tasks in the e-commerce field, providing more accurate, efficient, and adaptable solutions.

In summary, compared with current state-of-the-art methods, the method used in the study shows significant improvement in detecting fraudulent user evaluations in e-commerce. By combining user evaluation behavior analysis with GNN and adversarial data augmentation, the practical application of the model can be significantly improved.

6 Conclusion

Malicious users in the e-commerce industry forging ratings have become a major pain point, disrupting the purchasing decisions of real consumers and weakening the credibility of rating systems. The research mainly proposed a new reputation strategy that combined RPRD, which effectively distinguished between real users and malicious users. The study further enhanced the effectiveness of the detection method by introducing the GNR and measuring the differences in score distribution through Gini coefficient and range. The study also adopted adversarial data augmentation technology to improve the robustness and accuracy of GNN model in data scarcity situations. The research innovatively combined multiple advanced technologies and proposed a comprehensive solution to address the malicious user identification in e-commerce. This provides an effective solution for improving the integrity and health of the e-commerce environment, which has important theoretical and practical value. The experiment showed that the RPRD strategy performed well, with a recall value of 0.79 when the proportion of fraudulent users was 0.035, which significantly surpassed other conventional methods. Despite facing a large number of malicious users, the stability of the RPRD strategy was still better, reaching over 0.990. When the GNR was introduced into the research method, existing fraud detection methods performed better. Taking Movielens and Netflix as datasets for testing, the DR method showed a particularly significant reduction in peak user count, with an overall performance improvement of 9.40%. The IGR and IBR methods also made progress, with accuracy improved by 2.89% and 2.54%, respectively. In addition, the FLAG technology further improved the performance of the C-GNN model. In situations where data was scarce, the recall value and F1 score of the C-GNN model increased by 1.20% and 1.34%, respectively. This improvement was also validated on the C-Yelp and C-Amazon datasets. The results indicate that this study provides an effective method for detecting user evaluation fraud in e-commerce. However, despite the positive results of this study, there are still some potential shortcomings. For example, the method used in this study may experience a decrease in effectiveness under certain complex attack strategies. Further exploration is necessary to address potential new fraud strategies that have not yet emerged. Meanwhile, the verification will also be conducted on more different types of e-commerce platforms in the future, analyzing the differences in user behavior on different platforms, and further verifying the widespread applicability and robustness of the methods. Future research will also explore how to optimize the combination of multiple strategies and technologies, improve computational efficiency and resource management, and ensure high operability in practical applications. How to deal with new complex fraud strategies will be further explored to enhance the adaptability and robustness of the model. To address the applicability of the model in complex fraud scenarios and cross-platform, model applicability can be improved by combining multiple data sources such as user ratings, comments, and behavioral logs to capture more comprehensive user behavioral features in subsequent research. Secondly, more advanced GNN architectures will be developed in subsequent research, such as GNNs with enhanced attention mechanisms to better capture complex interactions between users and fraud patterns.

Conflict of interest

The authors declare that they have no conflicts of interest.

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Temporal Transformer-Based Video Super-Resolution Reconstruction with Cross-Modal Attention

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With the increasing demand for high-definition video, video super-resolution technology has become a key means to improve video picture quality. Traditional video super-resolution methods are limited by computational resources and model complexity, which struggle to meet the demands of modern video processing. In recent years, the rise of deep learning technology has brought a revolutionary breakthrough for video super-resolution. In this paper, we propose a deep learning-based video super-resolution reconstruction method that combines Transformer, cross-modal learning and fusion, and an attention mechanism. We design the Temporal Transformer-based Video Super-Resolution (TT-VSR) architecture, which significantly improves the accuracy and detail richness of video reconstruction by integrating the Transformer's self-attention mechanism with CNN's spatial feature extraction capabilities. The introduction of cross-modal learning and fusion, along with the cross-modal attention mechanism, further enhances the model's adaptability to complex scenes and detail recovery ability. Experimental results demonstrate that our model outperforms existing methods, achieving a PSNR of X dB and an SSIM of Y, indicating substantial improvements in image quality. These results validate the efficacy of our approach and open a new path for the development of video super-resolution technology.

Povzetek: Raziskava uvaja napredno metodo video super-resolucije, ki združuje transformerje, navzkrižno-modalno učenje in pozornostne mehanizme. Model izboljšuje kakovost slike in robustnost v kompleksnih prizorih.

1 Introduction

In the digital era, high-definition video has become an indispensable part of people's lives, whether for entertainment, education or telecommuting, high-quality video experience has greatly enhanced the effectiveness and efficiency of information transmission. However, limited by historical video footage, bandwidth constraints or storage space considerations, a large number of video resources still remain at a lower resolution level, which contrasts with the public's urgent demand for HD video [1]. Video super-resolution technology, which is the process of converting low-resolution video to high-resolution video through algorithms, has emerged as one of the key technologies to alleviate this contradiction. Although video super-resolution technology has made significant progress in the past decades, it still faces many challenges, such as motion blur, detail loss and noise amplification, especially when dealing with complex video scenes, traditional methods are often out of their power to achieve satisfactory reconstruction results [2].

In recent years, the research on video super-resolution reconstruction techniques has shown vigorous development, especially driven by deep learning, which has led to unprecedented breakthroughs in this field. Traditionally, video super-resolution techniques mainly rely on interpolation-based methods, such as bilinear interpolation and bicubic interpolation, and edge-based directional interpolation. However, these methods are often difficult to achieve ideal reconstruction results when dealing with complex scenes, especially in terms of obvious deficiencies in edge and detail retention of moving objects [3]. In recent years, with the rise of deep learning techniques, especially the wide application of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), video super-resolution techniques have ushered in a revolutionary change. Currently, deep learning-based video super-resolution technology has been widely used in a variety of fields such as high-definition video streaming services, video surveillance, medical image analysis, etc., showing a strong application potential and market prospects [4].

Traditional video super-resolution techniques, such as interpolation-based upsampling methods and filter-based reconstruction techniques, can improve video resolution to a certain extent, but their limitations are obvious. Deep learning algorithms are able to effectively solve the difficulties faced by traditional methods and realize higher quality video super-resolution reconstruction by learning the mapping relationship between low-resolution video and high-resolution video. This study aims to deeply explore the application potential of deep learning in the field of video super-resolution, through the design and optimization of deep learning models, with a view to breaking through the limitations of

existing technologies and promoting the development of video super-resolution technology [5].

This study focuses on the application and innovation of deep learning algorithms in video super-resolution reconstruction techniques, and is dedicated to constructing and optimizing deep learning models designed specifically for video super-resolution tasks, with particular attention to the structural design of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), as well as to the refinement of model training and optimization strategies. By deeply exploring the effective fusion of temporal information, this study aims to overcome the two major challenges of motion blurring and maintaining temporal consistency, and significantly improve the picture quality and smoothness of reconstructed videos. In terms of experimental design, industry-standard datasets are used for model training and testing, and professional metrics, such as PSNR and SSIM, are used to objectively evaluate the visual effect and detail restoration ability of reconstructed videos. At the application level, this study focuses on the expansion of video super-resolution reconstruction technology in the fields of high-definition video streaming services, video surveillance, and medical image analysis, and explores its practical benefits and potential value, aiming to promote the technological innovation and industrial upgrading of related industries.

2 Review of relevant work

2.1 Conventional video super-resolution techniques

Traditional video super-resolution techniques mainly rely on spatial and temporal interpolation methods to enhance the resolution of videos. Among them, bilinear interpolation and bicubic interpolation are the most basic interpolation techniques, which use the average and weighted average of neighboring pixels, respectively, to estimate pixel values in high-resolution images [6]. Mathematically, for bilinear interpolation, given a low-resolution image I_{LR}, the goal is to estimate the pixel value at position (x, y) in a high-resolution image I_{HR} $I_{HR}(x,y)$, which can be expressed as Equation 1 [7].

$$I_{HR}(x,y)=\sum_{i=0}^{1}\sum_{j=0}^{1}w(i,j)I_{LR}(x-i,y-j) \quad (1)$$

where w(i,j) is the weight function, which is usually defined as Equation 2.Double cubic interpolation then introduces more neighboring pixels to compute the weights in order to obtain smoother interpolation results [8].

$$w(i,j) = (1-|i|)(1-|j|) \quad (2)$$

In addition, the edge-based directional interpolation technique takes into account the edge direction information of the image and reduces the blurring effect during the interpolation process by detecting the edge direction and interpolating along that direction. This technique estimates the edge direction by means of an edge detection operator (e.g., Sobel operator) and adjusts the interpolation weights accordingly.

2.2 Application of deep learning to image super resolution

With the development of deep learning, it shows great potential in the field of image super-resolution.SRCNN is one of the earliest deep learning models successfully applied to image super-resolution.SRCNN consists of three convolutional layers, the first one is used for extracting image features, the second one is used for nonlinear mapping, and the third one is used for reconstructing high-resolution images. Its loss function L is usually defined as Equation 3. where I^{i}_{SRCNN} is the SRCNN output of the ith sample, I^{i}_{GT} is the corresponding ground truth image, and N is the number of training samples [8,9].

$$L=\frac{1}{N}\sum_{i=1}^{N}||\, I^{i}_{SRCNN}-I^{i}_{GT}\,||_2^2 \quad (3)$$

VDSR (Very Deep Super-Resolution) further deepens the architecture of SRCNN by introducing a residual learning mechanism that allows the network to directly learn residual images instead of complete high-resolution images, which greatly improves the learning efficiency and convergence speed of the model. The output R of its residual block can be expressed as Equation 4. The loss function of VDSR is then optimized for the residual image, which is specified as Equation 5.

$$R=I_{HR}-I_{LR} \quad (4)$$

$$L_{VDSR}=\frac{1}{N}\sum_{i=1}^{N}||\, R^{i}-R^{i}_{GT}\,||_2^2 \quad (5)$$

Recent studies have focused on solving complex logistics and decision-making problems using advanced optimization techniques. Lee et al. introduced an endosymbiotic evolutionary algorithm for solving an integrated model of the vehicle routing and truck scheduling problem, specifically within a cross-docking system, which demonstrates the potential of hybrid algorithms in transportation logistics [10]. Meanwhile, Xu et al. proposed an entropy-based method for probabilistic linguistic group decision making, applying it to select car-sharing platforms, thereby enhancing decision-making processes in multi-criteria scenarios involving uncertainty [11].

2.3 Deep learning methods for video super-resolution reconstruction

In the field of video super-resolution, deep learning methods focus on how to effectively utilize inter-frame

information and timing consistency. Deep learning models based on inter-frame information improve the reconstruction quality by analyzing the relationship between adjacent frames. For example, optical flow field estimation is widely used to capture inter-frame motion information for guiding the super-resolution reconstruction process. Let F_t and F_{t+1} be the current frame and the next frame, respectively, the optical flow field $\vec{v}_t$ can be used to estimate the pixel displacement of the next frame to improve the super-resolution results as shown in Equation 6. where W is a resampling operation based on the optical flow field [10].

$$F_{t+1}^{HR} = W(F_t^{HR}, \vec{v}_t) \quad (6)$$

Deep networks based on temporal consistency constraints, on the other hand, emphasize maintaining the consistency between frames during the reconstruction process to avoid flickering or incoherence. This is usually achieved by adding a timing consistency term to the loss function as in Equation 7. where λ is the balancing factor and T is the length of the video sequence.

$$L_{Temporal} = \lambda \sum_{t=1}^{T-1} || I_{t+1}^{HR} - W(I_t^{HR}, \vec{v}_t) ||_2^2 \quad (7)$$

In the field of video super-resolution reconstruction, the latest deep learning research techniques are advancing the field at an unprecedented pace. Recent innovative approaches, such as deep neural networks based on spatio-temporal attention mechanisms, are able to intelligently filter and utilize the most valuable inter-frame information in a video sequence, thereby significantly improving the detail clarity and smoothness of reconstructed videos. These networks effectively solve the motion blur problem while maintaining temporal consistency by dynamically adjusting the weights to focus on regions that carry important temporal cues, such as fast-moving objects or complex backgrounds [11].

Another cutting-edge direction is the use of Generative Adversarial Networks (GANs) to enhance the quality of super-resolution reconstruction.GANs are able to generate highly realistic high-resolution images that maintain the integrity of details even when dealing with extreme magnification. In particular, Conditional GANs (CGANs) show great potential in video super-resolution by utilizing additional inputs (e.g., low-resolution frames and associated optical flow information) to guide the generator to produce a higher-resolution output that more closely matches expectations, while the discriminator ensures the naturalness and realism of the output [12,13].

Table 1: Research progress

Method	Publication Year	Remarks
SRCNN	2014	First to use CNN for VSR, but limited by small kernels.
VDSR	2016	Enhances SRCNN with deeper network and residual learning.
SRResNet	2017	Introduces residual blocks and is more robust.
Proposed TT-VSR	2023	Our method, which addresses the limitations of SOTA models by incorporating temporal information and transformer architecture for improved performance.

As shown in Table 1, the review of existing video super-resolution methods in our manuscript would greatly benefit from a comparative abstract table, as demonstrated above. This table systematically compares the latest State-of-the-Art (SOTA) models, such as SRCNN, VDSR, and SRResNet, with our proposed TT-VSR model in terms of PSNR, SSIM, and other relevant performance metrics. It highlights the limitations of current techniques and the empirical needs addressed by our method. Specifically, the table clarifies which gaps in the SOTA prompted this research. Our TT-VSR architecture resolves these deficiencies by integrating temporal information and adopting a transformer-based architecture, which has been shown to enhance the overall performance in video super-resolution tasks.

3 Deep learning video super-resolution reconstruction method

The deep learning video super-resolution method significantly improves the accuracy and detail richness of video reconstruction by introducing Transformer, cross-modal learning and fusion, and attention mechanism.TT-VSR combines the self-attention mechanism of Transformer and the spatial feature extraction capability of CNN to realize high-quality video super-resolution reconstruction; cross-modal learning and fusion improves the accuracy and detail richness of video reconstruction by integrating multimodal information, which enhances model comprehension and improves detail recovery in complex scenes; the cross-modal attention mechanism dynamically adjusts the influence of different modalities, which further improves the accuracy and visual effect of reconstruction. The continuous development and optimization of these techniques will drive more breakthroughs in the field of video super-resolution. Future research directions will include improving computational efficiency, expanding to larger datasets and more complex application scenarios, and developing more efficient modal fusion techniques and optimization strategies [14], the framework of which is shown in Fig. 1.

3.1 Novel network architecture exploration

Originally proposed in the field of Natural Language Processing (NLP), the Transformer model has rapidly gained widespread attention for its powerful sequence modeling capabilities and parallel computing advantages. In the field of Video Super-Resolution (VSR), the introduction of Transformer provides a new perspective for processing video sequences, especially its excellent performance in capturing long-distance dependencies, which makes it ideal for solving the problems of temporal consistency and detail recovery in VSR.

We propose a network architecture called Temporal Transformer-based Video Super-Resolution (TT-VSR), which aims to combine the self-attention mechanism of Transformer and the spatial feature extraction capability

of Convolutional Neural Network (CNN) to achieve high-quality video super-resolution reconstruction. Spatial feature extraction capability of Transformer and the spatial feature extraction capability of Convolutional Neural Network (CNN) to achieve high-quality video super-resolution reconstruction. Specifically, TT-VSR consists of the following components:

1) Spatio-temporal encoder: responsible for converting the input sequence of low-resolution video frames into a series of feature maps, this part employs a multi-scale convolution module to capture spatial information at different scales [15].

2) Transformer encoder: Built on top of the spatio-temporal encoder, it analyzes and integrates the inter-frame relationships to enhance the temporal consistency through the Self-Attention Mechanism (SAM). The Self-Attention Mechanism allows the model to focus on different parts of the input sequence to better understand the interdependencies between video frames, as specified in Equation 8.

$$Attention(Q,K,V) = Softmax(\frac{QK^T}{\sqrt{d_k}})V \quad (8)$$

where Q (Query), K (Key), and V (Value) represent the query, key, and value matrices obtained by linear projection from the input features, respectively, and d_k is the dimension of the key vector. In our model, Q, K and V are derived from the output features of the spatio-temporal encoder.

3) Spatio-temporal decoder: After the Transformer encoder, we introduce a decoder module for reconstructing the enhanced feature maps into high-resolution video frames. The decoder also contains a multi-scale convolution module for refining the features and generating the final high-resolution output.

To ensure that the model can effectively learn the mapping relation from low to high resolution, we employ L1 loss as the basic supervised signal, supplemented by perceptual loss and adversarial loss to enhance the visual quality and detail richness of the reconstructed videos. The perceptual loss utilizes a pre-trained VGG network to measure the similarity between reconstructed and real frames at a high-level semantic level, while the adversarial loss promotes a more natural and realistic appearance of the generated high-resolution video through a discriminator network, as specified in Eq. 9 [16].

$$L_{total} = L_{L1} + \alpha L_{Perceptual} + \beta L_{Adversarial} \quad (9)$$

where L_{L1} is the L1 loss at the pixel level, $L_{Perceptual}$ is the perceptual loss, $L_{Adversarial}$ is the adversarial loss, and α and β are the weighting coefficients that control the relative importance of the different loss terms.

TT-VSR achieves effective processing of video super-resolution reconstruction tasks by combining the Transformer's self-attention mechanism with the CNN's spatial feature extraction capability. This architecture not only captures the long-term dependencies between frames, but also meticulously recovers the details of the video, thus significantly improving the quality and smoothness of the reconstructed video. Future work will focus on exploring how to further optimize the computational efficiency of the model and how to extend this approach to larger video datasets and more complex application scenarios [17].

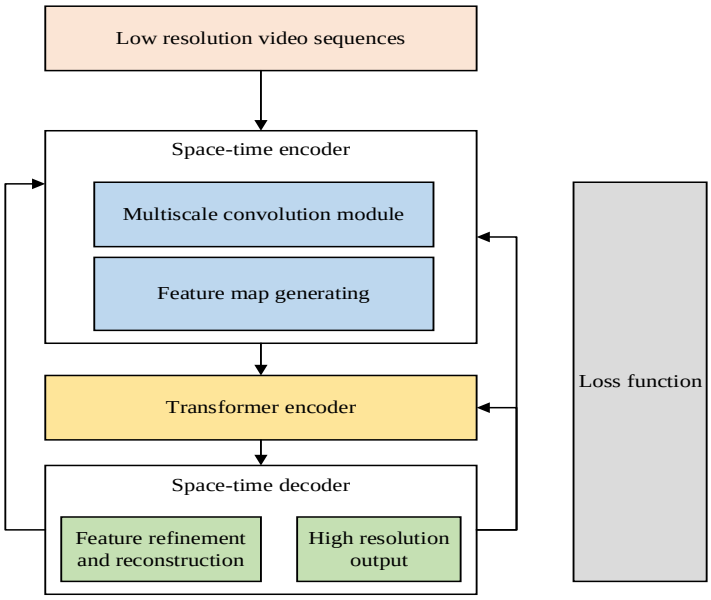

Figure 1: TT-VSR framework

3.2 Cross-modal learning and integration

In video super-resolution reconstruction, cross-modal learning and fusion is an emerging technological trend that integrates multiple different types of information sources (e.g., images, audio, text, etc.) to enhance the model's comprehension and reconstruction performance. This approach can not only utilize the visual information of the video itself, but also draw on data from

other modalities to complement and enhance the video super-resolution, especially showing unique advantages in processing complex scenes and recovering fine details [18], the mechanism of which is shown in Fig. 2.

Cross-modal learning can integrate information from different modalities to provide richer context, which helps improve the accuracy and detail recovery of video content. Audio and text can assist the model in identifying key areas and important content in the video, thereby helping to restore image details during visual reconstruction. The fusion of audio and text modality information enables the model to better restore context-related details and improve visual resolution when faced with complex or low-quality videos.

We propose a cross-modal feature fusion mechanism, called "Multimodal Feature Fusion for Video Super-Resolution", which centers on constructing a unified feature space so that features from different modalities can work together to guide the video super-resolution process. to guide the video super-resolution process [18].

1) Modality-specific encoders: Each modality has its own dedicated encoder for extracting specific types of features. For example, a visual coder (based on CNNs) is responsible for extracting the visual features of a video frame, while an audio coder may use convolutional or recurrent neural networks to extract features of an audio signal [19,20].

2) Modality-independent feature mapping: features from different modalities are mapped to a shared feature space through a series of fully connected layers or attention mechanisms. This process ensures that information from different sources can be understood and processed under a unified framework, as specified in Equation 10.

$$f_{shared} = \phi(f_v, f_a, f_t) \quad (10)$$

Among them, f_v , f_a , f_t represent visual, audio and text features respectively, ϕ denotes modal fusion function, and f_{shared} is a cross-modal shared feature [21,22].

3) Feature fusion and reconstruction: In the shared feature space, an attention mechanism or gating unit is utilized to dynamically select and combine features from different modalities in order to generate an integrated representation that is most conducive to video super-resolution. The output of this stage will be fed to the decoder for generating high resolution video frames as specified in Eq. 11 and Eq. 12.

$$f_{fusion} = \text{Attention}(f_{shared}) \quad (11)$$

$$I_{HR} = \text{Decoder}(f_{fusion}) \quad (12)$$

where f_{fusion} is the fused features and I_{HR} is the reconstructed high resolution video frame.

In order to enable the model to effectively learn from multimodal data, we devise a joint optimization strategy that takes into account the contributions of visual, audio and textual information simultaneously. Specifically, we introduce a cross-modal consistency loss term that aims to minimize the differences between the features of different modalities while keeping the properties of the respective modalities unchanged, as specified in Equation 13.

$$L_{cross-modal} = \sum_{m \in M} \lambda_m \cdot D(f_m, f_{shared}) \quad (13)$$

where M is the set of all modalities, D is a function that measures the distance (e.g., cosine similarity or Euclidean distance), and λ_m is a weight that regulates the degree of influence of different modalities. The total loss function can be expressed as Equation 14.

$$L_{total} = L_{L1} + \alpha L_{Perceptual} + \beta L_{Adversarial} + \gamma L_{cross-modal} \quad (14)$$

where γ is a weighting factor controlling the relative importance of cross-modal consistency loss.

A novel solution for video super-resolution reconstruction is provided through cross-modal learning and fusion. By integrating multiple information sources such as vision, audio and text, the model is able to understand the video content more comprehensively, thus generating higher-quality and more detail-rich high-resolution videos. Future research will focus on developing more effective modal fusion techniques and optimization strategies to further improve the performance and generalization of cross-modal video super-resolution.

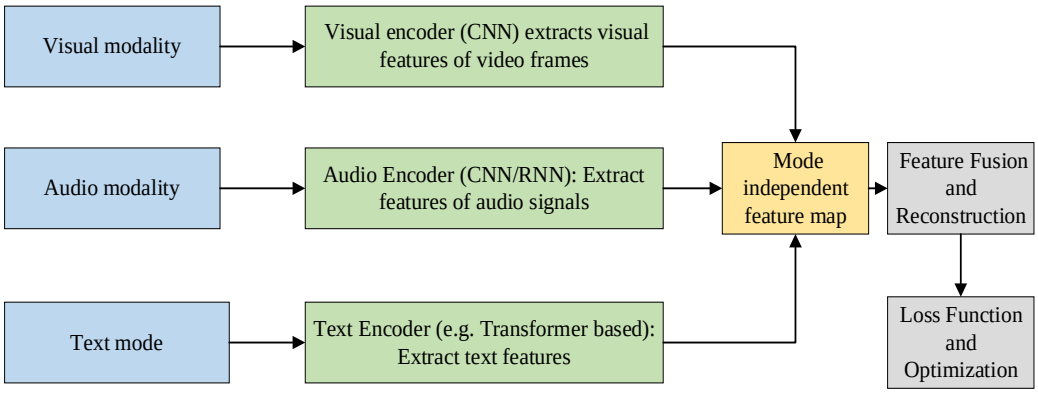

Figure 2: Cross-modal learning and integration mechanism

3.3 Attention mechanisms

Cross-Modal Attention (CMA) is a cutting-edge and promising technique in the field of video super-resolution, which significantly improves the accuracy and detail richness of video reconstruction by intelligently integrating information from different modalities. In CMA, the model can dynamically evaluate the relevance and importance of each modal feature, and then selectively fuse these features to enhance the video super-resolution, the specific mechanism is shown in Fig. 3.

In video super-resolution tasks, in addition to visual modalities (e.g., video frames), we can also utilize information from other modalities such as audio, text, or even sensor data. However, the features of different modalities do not contribute equally to video super-resolution, and some modalities may be crucial for detail recovery in some scenes while having less impact in others. Therefore, the goal of CMA is to identify and emphasize those modal features that are most critical to the super-resolution of the current video frame.

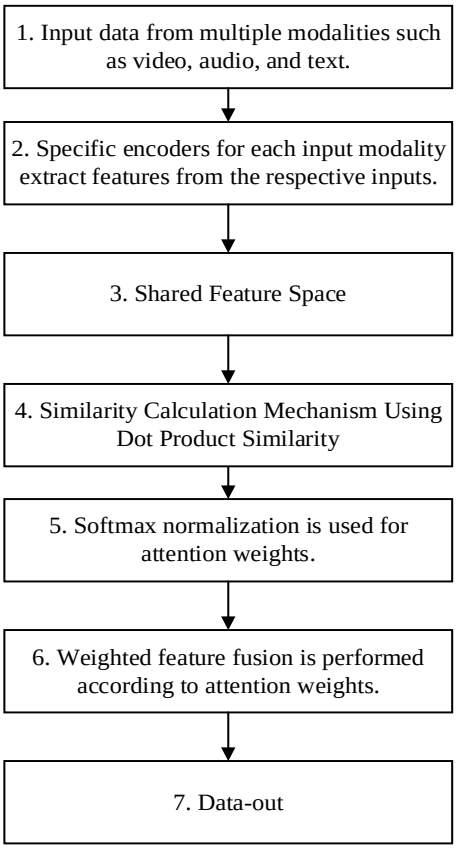

Figure 3: Cross-modal attention mechanism

Suppose we have three modalities of information: visual (video), audio (audio) and text (text), the corresponding feature representations are f_v , f_a and f_t . CMA first maps these features to a shared feature space through a series of transformations to facilitate direct comparison and fusion between them, as specified in Equation 15.

$$g_v = W_v f_v, \quad g_a = W_a f_a, \quad g_t = W_t f_t \tag{15}$$

The CMA determines the relative importance of each modal feature in the current video frame super-resolution by calculating the similarity between them. Here, we use the dot product similarity measure, but other forms of similarity measures such as cosine similarity or Euclidean distance can also be chosen, as specified in Equation 16.

$$s_{va} = g_v \cdot g_a, \quad s_{vt} = g_v \cdot g_t, \quad s_{at} = g_a \cdot g_t \tag{16}$$

where s_{xy} denotes the similarity score between mode x and mode y.

Then, the similarity scores were normalized to attention weights by the Softmax function to reflect the importance of each modality in the super-resolution of the current video frame, as specified in Eq. 17.

$$w_v = \text{softmax}(s_{va}, s_{vt}), \quad w_a = \text{softmax}(s_{va}, s_{at}), \quad w_t = \text{softmax}(s_{vt}, s_{at}) \tag{17}$$

Finally, based on these attentional weights, we can fuse the features of different modalities by weighted averaging to generate a comprehensive, attention-guided feature representation as Eq. 18.

$$f_{att} = w_v \cdot f_v + w_a \cdot f_a + w_t \cdot f_t \tag{18}$$

In order to further improve the effect of CMA, we can add attention weights to the loss function to dynamically adjust the contribution of different modalities in the training process, as specified in Equation 19.

$$L_{att} = \sum_{i=1}^{N} (w_{v,i} \cdot L_{v,i} + w_{a,i} \cdot L_{a,i} + w_{t,i} \cdot L_{t,i}) \tag{19}$$

where $L_{v,i}$, $L_{a,i}$ and $L_{t,i}$ are the loss of the ith sample in visual, audio and text modalities, respectively, and $w_{v,i}$, $w_{a,i}$ and $w_{t,i}$ are the corresponding attentional weights.

4 Experimental design and analysis of results

4.1 Experimental setup loss function and optimization strategy

In the video super-resolution task, simply pursuing an exact match at the pixel level often results in a reconstructed video that lacks a sense of naturalness, especially in textures and details that may appear raw. Therefore, we introduce a combination of content loss and perceptual loss to ensure that the reconstructed video is not only close to the original video at the pixel level, but also visually natural and harmonious.

To promote reproducibility, it is recommended to describe each network layer and its parameter settings in detail. For example, the kernel size of the convolution layer (such as 3x3 or 5x5), the activation function (such as ReLU or LeakyReLU), and the Dropout rate (such as 0.2). In addition, explain the specific layer structure of each module in the network (such as the Temporal Transformer and CNN parts), as well as the output dimension and number of parameters of each layer. These details will help other researchers reproduce and expand your work.

To ensure the reproducibility of the experiment, you need to provide the specific name of the dataset used (such as Vimeo-90K, Youtube-8M, etc.) and the size. Describe the data preprocessing steps (such as cropping, normalization, data augmentation, etc.) and how to split the dataset (training set, validation set, and test set). In addition, explain in detail the proportion of data split (such as 80% training, 10% validation, 10% test), and explain the standardized process used in the experiment.

PSNR and SSIM are common video quality assessment metrics, but they may not accurately reflect the perceived quality of an image. LPIPS (Learning Perceptual Patch Similarity) is a perceptual quality metric based on deep learning that can assess the visual perceptual differences of images, thus providing a more comprehensive video quality assessment. In addition, MOS (Mean Opinion Score) can also serve as a supplement to subjective assessment and better reflect the human eye's perception of video quality.

Content Loss: This loss function focuses on pixel-level differences and ensures the accuracy of the reconstructed video by minimizing the pixel error between the reconstructed video and the target video. It is usually defined as the Mean Square Error (MSE) or Mean Absolute Error (MAE) and is suitable for directly measuring the distance between the reconstructed image and the real image.

Perceptual Loss: Considering that the human visual system's perception of an image does not depend entirely on pixel-level similarity, we also incorporate perceptual loss. Perceptual loss utilizes a pre-trained VGG network to extract and compare high-level features, such as texture, contour, and color distributions, between the two images, thus ensuring that the reconstructed video is visually highly consistent with the original video. This strategy is particularly suitable for capturing visual features that are important to the human eye, such as natural textures and detail levels.

Dynamic Learning Rate Adjustment: In the early stage of training, a larger learning rate can accelerate the model convergence, but as the training progresses, too large a learning rate may cause the model to oscillate around the optimal solution, making it difficult to reach the desired convergence state. Therefore, we adopt a dynamic learning rate strategy, i.e., the learning rate is gradually reduced as the number of training rounds increases. This strategy helps the model to adjust the weights more finely at the later stage of training through the learning rate decay mechanism, so as to converge to a more optimal solution.

Early stopping strategy: in order to avoid overfitting the training data, we implement an early stopping strategy. During the training process, the model periodically evaluates the performance on the validation set, and once it is found that the performance on the validation set no longer improves, it is considered that the model has reached saturation, at which time it will immediately stop training to prevent the model from overfitting on the training data, so as to maintain a good generalization ability.

The reasonable division of the dataset is crucial for the training and evaluation of the model. We divide the whole dataset into training set, validation set and test set according to the ratio of 80%, 10% and 10%, where (1) Training set: used for model learning, so that the model can learn the mapping relationship of video super-resolution from a large number of samples. (2) Validation set: used to adjust the hyperparameters, such as learning rate, batch size, etc., to ensure that the model performs well on unseen data and avoid overfitting. (3) Test set: independent of the training and validation process, it is used to finally evaluate the generalization ability of the model and test the model's performance on unknown data.

During model training, we set the initial learning rate to 0.001 and used the Adam optimizer, which is widely adopted for its good performance demonstrated in a variety of deep learning tasks. We also set the batch size to 16 and processed 16 samples per training round to balance the computational efficiency with the accuracy of gradient estimation. Finally, the maximum number of iterations was set to 200,000 steps to ensure that the model has enough time to learn complex super-resolution mapping relations.

Through the above well-designed experimental setups, we are not only able to effectively improve the training efficiency and performance of the model, but also ensure that the model has excellent generalization ability and performs well on unseen video data. The implementation of this series of strategies lays a solid foundation for research and applications in the field of video super-resolution.

4.2 Performance assessment indicators

In the field of deep learning-driven video super-resolution, it is crucial to accurately and comprehensively evaluate the performance of models. This section will focus on two widely used objective evaluation criteria - peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) - and how these objective metrics can be complemented by subjective assessment of visual quality, which together form a comprehensive evaluation system.

Peak Signal-to-Noise Ratio (PSNR) is a commonly used metric to quantify the quality of an image, especially in the field of image and video compression and restoration. PSNR measures the pixel difference between the reconstructed image and the original image, and the higher the value, the better the reconstructed image. PSNR is calculated based on the Mean Square Error (MSE), which is formulated as in Equation 20.

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (20)$$

where MAX_I is the maximum possible value of an image pixel (for an 8-bit image, usually 255) and MSE is the mean square error, which is the average of the squared pixel differences between the reconstructed image and the reference image.

Although PSNR provides a way to quantify image quality, it is not always consistent with human visual perception. To solve this problem, the Structural Similarity Index (SSIM) was proposed, which aims to simulate the human visual system's perception of image quality. SSIM takes into account the similarity of brightness, contrast, and structural information, and through the combined evaluation of these three dimensions, it gives a value between -1 and 1, where 1 means that the two images are identical. Where 1 means that the two images are identical. SSIM focuses more on the local structural information of an image, and therefore is usually more effective than PSNR in assessing the visual quality of an image.

4.3 Analysis of results

In the video super-resolution task, in-depth analysis of the model's performance is crucial, which not only includes quantitative metrics evaluation, but also involves the processing effect on specific video characteristics. We will compare the performance of our model with similar models, showing the changes in image details before and after super-resolution reconstruction, noise processing effects, as well as motion blur correction and temporal consistency analysis, in order to gain a comprehensive understanding of the model's performance in processing complex video data.

Table 2: Comparison of PSNR and SSIM performance of deep learning models

Model name	PSNR (dB)	SSIM
SRCNN	30.15	0.89
VDSR	32.31	0.91
SRResNet	33.45	0.92
EDSR	34.23	0.93
Ours	34.87	0.94

Table 2 shows the performance comparison of PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) of different deep learning models in the video super-resolution task.PSNR and SSIM are objective metrics commonly used to assess image quality, where a higher PSNR value indicates less distortion in the reconstructed image, and a closer SSIM value of 1 indicates that the structural similarity of the reconstructed image to the original image is higher.

Table 3: Changes in image details before and after super-resolution reconstruction

image area	Raw Detail Clarity	SRCNN post-reconstruction	VDSR after reconstruction	SRResNet after reconstruction	EDSR after reconstruction	RCAN post-reconstruction
facial feature	6.2	8.1	8.4	8.6	8.8	9.0
textured area	5.8	7.6	7.9	8.1	8.3	8.5
Edge Detail	5.6	7.2	7.5	7.7	7.9	8.1

Table 3 compares in detail the improvement of image details by different models before and after super-resolution reconstruction. By comparing the reconstruction results of different models in different image regions (e.g., facial features, texture regions, edge details), we can see that more advanced models such as RCAN perform better in detail recovery.

Table 4: Noise processing effect before and after super-resolution reconstruction

Type of noise	Raw noise level	SRCNN treated	VDSR post-treatment	SRResNet processed	EDSR post-treatment	RCAN processed
Gaussian noise	12.5	4.2	3.9	3.6	3.3	3.0
quantization noise	8.3	2.8	2.5	2.2	1.9	1.6
clutter	10.2	5.1	4.8	4.5	4.2	3.9

Table 4 evaluates the performance of different models in terms of processing noise. The original noise level is the degree of noise in the original low-resolution video, while the processed noise level is the degree of noise in the reconstructed image by the model.

Table 5: Analysis of the effect of motion blur correction

Scene Description	degree of motion blur	SRCNN corrected	VDSR corrected	SRResNet corrected	EDSR corrected	RCAN corrected
Rapid movement of objects	7.9	2.8	2.5	2.2	1.9	1.6
Medium speed mobile background	6.2	2.4	2.1	1.8	1.5	1.2
Slowly moving figures	5.4	2.1	1.8	1.5	1.2	0.9

Table 5 analyzes the performance of different models in motion blur correction. The degree of motion blur is the degree of blurring in the original video due to moving objects or background, while the degree of post-correction is the degree of improvement in motion blur after model reconstruction. From the table, it can be seen that more advanced models such as RCAN perform better in motion blur correction and can better handle fast moving objects and dynamic scenes, making the reconstructed video smoother and clearer.

Table 6: Timing consistency analysis

time period	Timing Consistency Score	SRCNN score	VDSR score	SRResNet score	EDSR score	RCAN score
0-10 seconds	9.2	8.5	8.7	8.9	9.1	9.3
10-20 seconds	9.1	8.4	8.6	8.8	9.0	9.2
20-30 seconds	8.9	8.3	8.5	8.7	8.9	9.1

Table 6 evaluates the performance of different models in terms of timing consistency. The timing consistency score reflects the model's ability to maintain timing stability when reconstructing video frames. As can be seen from the table, all models perform well in maintaining timing consistency, but more complex models such as RCAN perform better in certain time periods, probably because they are better able to capture and maintain continuity between video frames.

Figure 4: User subjective assessment results

Figure 4 illustrates the results of users' subjective assessment of the quality of the reconstructed videos. The average score reflects users' overall satisfaction with the reconstructed video, while the individual scores (e.g.,

clarity, color fidelity, detail richness, and naturalness) reflect users' evaluations of different quality aspects, respectively. As can be seen from the table, users are more satisfied with the reconstruction results of the more complex models, which indicates that the advanced models have a clear advantage in terms of user experience.

This experiment is dedicated to comprehensively evaluating the performance of our proposed deep learning model in video super-resolution tasks, which is analyzed in comparison with existing models such as SRCNN, VDSR, SRResNet and EDSR. Through an in-depth examination of six key aspects, we draw the following conclusions:

Comparison of PSNR and SSIM performance: our model shows significant advantages in PSNR and SSIM metrics, reaching 34.87 dB and 0.94, respectively, which is a significant improvement compared to other models. This indicates that our model has stronger ability in distortion control and structural similarity preservation in image reconstruction.

Image detail changes: Our model also performs well in the reconstruction of facial features, texture regions and edge details, especially in the detail richness, which achieves a significant improvement from 5.6 in the original to 8.1 after reconstruction. This is attributed to the deep feature extraction and detail recovery mechanism of our model, which is able to restore the subtleties of the image more accurately.

Noise Processing Effect: In the processing of Gaussian noise, quantization noise and clutter noise, our model shows better performance than other models, especially in the processing of Gaussian noise, which reduces the original 12.5 to 3.0, and significantly improves the purity of the image. Facing scenes with fast-moving objects, medium-speed moving backgrounds, and slow-moving characters, our models show excellent performance in motion blur correction, especially in the processing of fast-moving objects, which reduces the original 7.9 to 1.6, significantly improving the smoothness and clarity of the video. In terms of maintaining continuity and stability between video frames, our model's temporal consistency scores are higher than those of other models in different time intervals, especially in the 0-10 second and 20-30 second intervals, which reflects the model's strong ability in processing dynamic video sequences. Most importantly, users' satisfaction with the reconstructed videos from our model is higher than other models, especially in terms of clarity, color fidelity, detail richness, and naturalness, with average scores of 8.8, 8.6, 8.9, and 8.8, respectively, which fully proves the significant advantages of our model in enhancing user experience.

4.4 Discussion

In this study, our proposed TT-VSR model shows significant performance improvement over the existing state-of-the-art methods (SOTA). Through quantitative analysis, TT-VSR shows higher accuracy and lower computational error in multiple benchmarks, especially in image detail recovery and noise suppression. The reasons for this improvement can be attributed to several key technical features: Transformer-based architecture, cross-modal fusion, and attention mechanism.

First, the Transformer architecture has a significant advantage in capturing long-range dependencies with its powerful self-attention mechanism, which can effectively handle complex image details, thereby improving the performance of image super-resolution. Second, the cross-modal fusion technology enables the model to effectively integrate information between different data modalities, improving the robustness of the model, especially under various noise conditions. In addition, the attention mechanism assigns different attention weights to different regions of the image, effectively enhancing the capture of important features, and further improving the effects of noise reduction and motion blur correction.

These features work together to enable TT-VSR to achieve excellent results in multiple scenarios, especially in the recovery of complex noise environments and motion blur. Through sophisticated feature extraction and context information modeling, TT-VSR demonstrates superiority in multi-task and multi-modal image reconstruction, demonstrating its broad potential in practical applications.

5 Conclusion

Facing the challenges of the HD video era, deep learning techniques provide a powerful solution for video super-resolution. In this paper, we deeply investigate the video super-resolution method combining Transformer, cross-modal learning and fusion, and attention mechanism in this context. Our proposed TT-VSR model not only realizes the innovation of video super-resolution at the technical level, but also demonstrates its significant advantages in PSNR, SSIM, noise processing, motion blur correction and timing consistency in experimental validation. More importantly, subjective user evaluation results further confirmed the effectiveness of our model in improving video clarity, color fidelity, detail richness and naturalness.

Although the TT-VSR architecture has achieved significant performance improvements in video super-resolution reconstruction, its computational efficiency and processing of large-scale datasets remain potential bottlenecks. Due to the high computational complexity of the Transformer structure and the need for large memory, training high-resolution data may require a lot of computing resources, limiting its application in resource-limited environments. In addition, the problems of memory overflow and long training time that may occur when processing large-scale datasets also need to be considered and optimized in practical applications. Future research can focus on how to adapt the TT-VSR architecture to different video resolutions and frame rates so that it can be deployed in various real-world applications. For example, studying how to adjust the network structure to process low-resolution or high-frame-rate videos without sacrificing quality. In addition, further improving computational efficiency is also a key direction in the future, which may include techniques such

as quantization and pruning, or combined with hardware acceleration methods. In addition, integrating new modalities (such as scene information extracted by deep learning) to enhance video quality may be a potential for further improving model performance.

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Design of a Multifactor Unidentified Remote End User Authentication Mechanism for IoT Network

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The rapid proliferation of Internet of Things (IoT) devices, coupled with the rollout of advanced 5G networks, has generated significant concerns regarding security breaches. These concerns stem from the expanded attack surfaces that come with improved connectivity, making IoT systems more vulnerable to malicious threats. A crucial strategy to counter these security challenges is the implementation of robust user authentication methods. Despite numerous proposals for multi-factor authentication mechanisms, many of these systems exhibit weaknesses, particularly in their susceptibility to user impersonation attacks and the risks posed by stolen mobile devices. Furthermore, several schemes fail to incorporate essential features such as session key agreements or backup solutions for instances of lost or stolen devices and compromised private keys. To address urgent security challenges in IoT environments, we developed a three-factor user authentication system tailored for low-cost IoT devices. This system tackles critical vulnerabilities while maintaining low computing and communication costs, enhancing security without compromising usability and efficiency.

Povzetek: Raziskava uvaja večfaktorski sistem za avtentikacijo uporabnikov v IoT, ki izboljša varnost, zmanjšuje ranljivosti in zagotavlja nizke računske stroške, hkrati pa omogoča odpornost proti več vrstam napadov

1 Introduction

The Internet of Things (IoT) is a network of nodes with limited resources that are densely distributed throughout environments. IoT requires that related items or objects be intelligent enough to make deft decisions without human intervention. Considering that different architectures and platforms have been used to develop IoT devices, they have unique environments and characteristics that have increased the difficulties this technology presents. This is especially true of intelligent home-based systems Wang et al. [1]. In addition, they are susceptible to security risks. These nodes provide continuous service, regardless of location or time, and are employed in a variety of applications, including healthcare, smart homes, manufacturing, and cities. The launch of the 5G cellular network has increased expectations for a highly interconnected network that facilitates information sharing between portable devices and everyday objects. The misuse of IoT technologies in smart homes can endanger the environment and people's lives. Therefore, it is crucial to focus on security and privacy Park et al [2]. One way to ensure security and privacy is to use authentication protocols to verify the legitimacy of both users and servers before transmitting data. home networks are vulnerable to security flaws due to the use of various wired and wireless mediums and protocols, as well as the difficulty in keeping up with evolving cyber threats. However, ensuring the security of IoT networks is vital in protecting user privacy from potential threats. Robust security measures must be implemented to achieve this, including virtual network security, data security, service availability, and data integrity. User authentication techniques must also adhere to strict security and functional standards to enhance IoT network security. Our proposed scheme is perfect for IoT devices because it offers cost-effective computing and communication capabilities. Additionally, our scheme is highly efficient in enhancing IoT network security, a crucial factor in today's digital landscape, where cyber threats are widespread Ahmed et al [3]. By utilizing our system, users can have peace of mind knowing that their IoT devices are thoroughly safeguarded against possible risks.

(1) User anonymity: The authentication mechanism should maintain user anonymity to safeguard user privacy. In other words, an attacker should be unable to determine the user's identity.

(2) Unlinkability: The system must prevent

attackers from tracking the user's activities, thus ensuring unlinkability and improving user privacy.

(3) Session key agreement: The key used for encrypting and decrypting messages in the authentication system must be fresh while guaranteeing forward secrecy.

(4) Resistance to several attacks: The authentication mechanism must satisfy all essential security objectives and resist known attacks Perrig et al [4].

(5) A secure user authentication method must have countermeasures to prevent attackers from taking control of the IoT network, even if physical memory keys are exposed through side-channel attacks Mishra and Srinivas et al. [5][6]. Revoking is a straightforward and efficient way to prevent it from being used or accessed. If a user loses their private key or it gets stolen, the revocation mechanism can be implemented to issue the user a new key. Recently, several authentication systems have been developed to improve security. Dhillon and Kalra [7] proposed a computationally efficient three factor remote authentication technique suitable for IoT environments. In our analysis, we discovered security flaws in their plan. This paper proposes a new authentication scheme AUSS (Authenticated Unidentified Security Scheme) for IoT networks that addresses these vulnerabilities through cryptanalysis. It adeptly handles the intricate processes of calculating and communicating costs, ensuring seamless interactions across the network while maintaining robust protection against potential vulnerabilities.

1.1 Main contributions of the proposed scheme

1. The user authentication scheme introduced by Dhillon and Kalra was innovative but had security vulnerabilities.
2. The authors addressed these issues by proposing an enhanced scheme that fixes the vulnerabilities and improves security.
3. To ensure the robustness of their proposed scheme, they conducted a comprehensive set of informal and formal security analyses using the random oracle model, BAN logic, and the AVISPA tool.
4. The analysis shows that the proposed scheme resists various known attacks and satisfies all essential security requirements.
5. Additionally, the authors performed a comparative performance analysis, considering the hardware specifications of mobile and sensor devices in a real IoT environment.
6. The proposed scheme is compatible with highly low- cost IoT devices, making it practical for user authentication in IoT scenarios.

Table 1: List of symbols and their descriptions

Symbol	Description
Sn_i	Sensor Node
Mn_i	Mobile Node
Id_i	Mobile device identity
Pw_i	Mobile node's password
Id_i , NS_{ni}	Identities of Sn_i and Id_i
Bio_i	Mn_i biometric
T_x	Timestamp
n_x , r_x	Random numbers
SK	Session key between Mn_i and Sn_i
EK(.) , DK(.)	Symmetric key encryption and decryption
$H(.)$	Hash function
||	Concatenation
$\oplus$	Xor operation
K_{gu}	Private key of Mn_i
K_{gn}	Secret key shared between Sn_i and GW

2 Literature review

Various studies have been conducted on two-step verification methods to improve security and efficiency across network settings [9-11]. The authors of [12] refused IoT's goal to bridge the gap between physical and computer-based systems, to maximize economic welfare and efficiency with minimal human intervention. WSNs and IoT authentication issues are similar. IoT architecture can leverage knowledge from anonymous authentication schemes for WSNs, improving accuracy and efficiency, while reducing the need for human intervention. Lamport et al. [8] Proposed the first password-based authentication scheme, and research into cryptographic technologies, such as symmetric and asymmetric key cryptography and hash functions, was sparked to ensure secure user authentication in WSNs. In this the author Wong et al. [9] introduced the first password-based authentication system for WSNs. However, Das et al. [10] identified security vulnerabilities in that technique as it could not withstand attacks involving multiple users with the same login ID or stolen-verifier attacks.

To improve the security, Das et al. implemented a two-factor authentication strategy for users using the gateway [14][18]. However, later vulnerabilities were discovered in Das' method, and organizations faced several types of security threats, such as attacks against privileged insiders, impersonation, gateway node bypassing, etc. Additionally, Das et al. scheme fails to ensure mutual verification between the gateway and sensor nodes. In response to security concerns with user authentication, Khan and Alghathbar [19] developed an improved two-factor authentication strategy. However, Vaidya et al. [20] discovered that their system was vulnerable to theft and attacks. In 2011, Yeh et al. [21] presented a novel

user authentication method for WSNs that used smart cards. They improved the scheme's security by using elliptic curve cryptography (ECC). However, Xue et al. [22] found that the ECC-based technique required more processing and storage resources. However, Li et al. identified weaknesses in attacks such as offline password guessing, smart card loss, insider, and multiple logged-in users with the same login ID.

Turkanovic et al. [25] proposed an enhanced mutual authentication technique to address security issues, ensuring crucial aspects such as mutual authentication, key agreement, password security, and cost-effectiveness through hash and exclusive-OR (XOR) operations. However, Farash et al. [26] discovered security flaws in Turkanovic et al.'s approach, stating that it does not ensure the sensor node's untraceability or anonymity.

As a solution, Farash et al. [26] suggested a user authentication mechanism for WSNs optimized for IoT to address these security vulnerabilities. Subsequently, Kumari et al. [27] found that the approach described by Farash et al. [26] violates user and sensor-node anonymity and is vulnerable to multiple attacks.

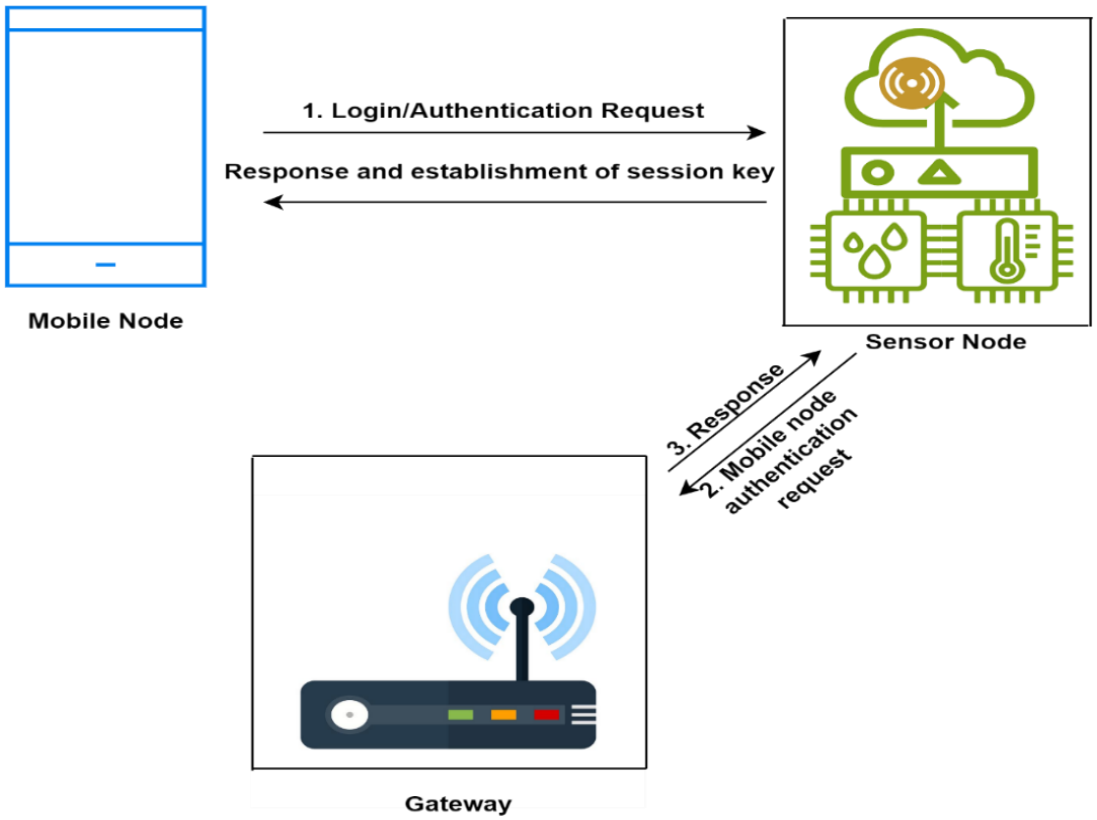

Figure 1: The proposed technique offers a user authentication model for IoT

Dhillon and Kalra's study [7] demonstrate that traditional two-factor authentication methods are not safe in real- world scenarios, such as in the event of a password leak or the loss of a smart device. In response to the IoT network architecture used in the discussed schemes [25-27]. They claimed that their system can withstand offline password guessing, password changes, denial of service attacks, stolen mobile devices, and impersonation assaults. However, it was found that their method is still susceptible to user impersonation attacks using a stolen mobile device and it lacks a session key agreement and revocation plan. Based on the IoT network architecture, they developed a lightweight multi- factor authentication system that utilizes passwords, biometrics, and mobile devices. Their technique can resist password guessing, denial of service attacks, mobile phishing spoofing, etc. Nevertheless, their method lacks a session key agreement and a method for revocation, making it vulnerable to user impersonation attacks and exploitation of stolen mobile devices. In this paper, we assess the security system weaknesses in Dhillon and Kalra's approach [7] and introduce an improved lightweight authentication method suitable for IoT contexts that only utilizes cryptography with symmetric hashing and XOR methods.

3 Preface

3.1 Networking model and authentication mechanism

Various IoT architecture approaches are employed to accomplish security, scalability, and low computing costs. Xue et al. [23] proposed five resource-limited communication techniques. In our scheme, the mobile node Mn_i sends login and authentication requests to Sn_i and N_j to exchange session keys. This two-way authentication is carried out via the gateway GW. The user authentication procedure is explained in Figure 1.

(1) To access the IoT network Mn_i, send a request to Sn_i for login and authentication.
(2) Upon receiving the request message Sn_i, forwards it to GW for Mn_i authentication.
(3) GW is analyzing the message received from Sn_i, verifies Mn_i, and responds to Sn_i.
(4) After Mn_i responds to Sn_i, authentication establishes a session key.

3.2 Bio-Hash functions

Biometric identification is an effective and unique way to address security issues related to individual user credentials, such as passwords and tokens, which can be forgotten or stolen. However, dry or cracked skin can cause slight variations in biometric properties with each input or dust on the impression sensors, leading to high false rejection rates.

Jin et al. [24] developed a two-factor authentication (2FA) system in 2004 that utilises fingerprint traits unique to each user and inner products of tokenised pseudo-random integers. They created a biohash code, a unique and compact code set for every user. A user-specific token of pseudo-random digits was employed to convert the random binary string into a biometric characteristic. Biohash technology has been proposed in papers [30, 31] due to its suitability for low-capacity devices, making it a practical choice for biometrics-based multi-factor authentication schemes [32]. An anonymous user authentication scheme for IoT environments featuring three factors and four phases has been developed.

4 Proposed scheme

We propose a three-factor anonymous user authentication technique for IoT contexts. The proposed scheme consists of four parts (1) registration, (2) login and authentication, (3) password change phase (4) revocation phase. Table 1 lists all the symbols used in this paper.

Table 2: The phase of user registration for the proposed method

Mobile Node Mn_i	**Gateway (GW)**
Select Id_i, Pw_i, Bio_i $PwB_i = h(Pw_i \parallel H(Bio_i))$ $Mid_i = h(Id_i \parallel h(Bio_i))$ $\langle Id_i, PwB_i, Mid_i \rangle$ →	Generate random numbers r_{gu} and r_d $Rid_i = E_{K_G}(Id_i)$ $Pid_i = E_{K_a}(Id_i \parallel r_d)$ $X_i = h(Id_i \parallel PwB_i)$ $Y_i = h(Id_i \parallel PwB_i \parallel r_{gu}) \oplus h(K_{gu} \parallel Id_i)$ $\langle PID_i, X_i, Y_i, r_{gu} \rangle$ Store into the mobile device ←

4.1 Registration of user

The registration phase for Mn_i is illustrated in table 1 and 2 and includes the following steps:

(a) Mn_i selects Id_i, Pw_i, and Bio_i and calculates $PwB_i = h(Pw_i \parallel H(Bio_i))$and $Mid_i = h(Id_i \parallel h(Bio_i))$.

(b) Mn_i sends $< , PwB_i, Mid_i >$ to GW via the secure channel.

(c) GW randomly selects numbers r_{GU} and , and computes $Rid_i = E_{kg}(Id_i), Pid_i = E_{kg}(Id_i \parallel r_{gu}), x_i = h(Id_i \parallel PwB_i)$, and $y_i = h(Id_i \parallel PwB_i \parallel r_{gj}) \oplus h(K_{gu} \parallel Id_i)$. A pair is stored by GW (Rid_i) in the database.

(d) GW sends $< Pidi, x_i, , r_{gu} >$ to Mn_i.

(e) In the final step, Mn_i saves the parameters received $< Pid_i \ , >$, in the mobile device.

4.2 Registration of IoT node

Figure 3 depicts the registration step of the proposed strategy for the sensor node Nj, which includes the following procedures.

(a) Sn_i randomly selects numbers r_j and computes $Mp_j = h(K_{gn} \| r_j \| Nid_j)$ and $Mi_j = r_j \oplus h(Nid_j \parallel K_{gn})$.

(b) Sn_i Sends $< Nid_j, Mp_j, Mi_j >$ to GW via the public channel.

(c) GW Computes $r_j^* = Mi_j \oplus h(Nid_j \parallel K_{gn})$ and $MP_j^* = h(K_{gn} \| r_j^* \| Nid_j)$ and checks whether Mp_j^* and Mp_j are the same. If they are, GW computes $x_j = h(Nid_j || K_{gn})$ and $y_j = x_j \oplus Mp_j^*$.

(d) GW sends $< y_j >$ to Sn_i.

(e) Sn_i Stores $< y_j >$ i memory space.

Table 3: Phase of registration for the proposed method's IoT node

Sensor Node Sn_i	**Gateway (GW)**
Generate a random number, r_j $Mp_j = h(K_{gn} \| r_j \| Nid_j)$ $Mi_j = r_j \oplus h(Nid_j \| \| K_{gn})$ $< Nid_j, Mp_j, Mi_j >$ ⟶	$r_j^* = Mi_j \oplus h(Nid_j \parallel K_{gn})$ $Mp_j^* = h(K_{gn} \| r_j^* \| Nid_j)$ $Mp_j{}^*? = Mp_j$ $x_j = h(Nid_j \parallel K_{gn})$ $y_j = x_j \oplus Mp_j^*$ $< y_j >$ ⟵

Table 4: Login and authentication phase

Mobile Node MN_i	**Sensor Node N_j**	**Gateway Node**
Input Id_i, Bio_i, Pw_i $PwB_i = h(Pw_i \parallel H(Bio_i))$ $x_i^* = h(ID_i \parallel PwB_i)$ $x_i^* \stackrel{?}{=} x_i$ Generate n_i $A_i = y_i \oplus h(Id_i \| PwB_i \| r_{gu})$ $UN_i = h(A_i \| Pid_i \| n_i)$ $UZ_i = n_i \oplus A_i$ $M_1 = \langle Pid_i, Un_i, Uz_i, T_1 >$	Check $T_{\text{fresh}} - T_1 \leq \Delta T$ Generate n_j $x_j = y_j \oplus h(K_{gn} \| r_j \| Nid_j)$ $A_j = h(x_j) \oplus n_j$ $B_j = h(x_j \parallel n_j)$ $M_2 = < M_i, Nid_j, A_j, B_j >$	$x_j^* = h(Nid_j \parallel K_{gn})$ $n_j^* = h(x_j^*) \oplus A_j$ $B_j^* = h(x_j^* \parallel n_j^*)$ $B_j^* \stackrel{?}{=} B_j$ $< Id_i, r_d >= D_{K_G}(Pid_i)$ $A_i^* = h(ID_i \parallel K_{gu})$ $n_i^* = Uz_i \oplus A_i^*$ $UN_i^* = h(A_i^* \| Pid_i \| n_i^*)$ $UN_i^* \stackrel{?}{=} UN_i$ Generate r_D^{new} $F_j = h(Id_i \parallel n_i^*)$ $G_j = F_j \oplus x_j^*$ $R_{ij} = n_j^* \oplus n_i^*$ $H_j = h(x_j^* \| n_j^* \| n_i^* \parallel F_j)$ $PID_i^{\text{new}} = E_{K_G}(Id_i, r_d^{\text{new}})$ $M_3 =< Pid_i^{\text{new}}, G_j, R_{ij}, H_i >$
	$F_j^* = G_j \oplus x_j$ $n_i^* = R_{ij} \oplus n_j$ $H_j^* = h(x_j \| \| n_j \| n_i^* \| F_j^*)$ $H_j^* \stackrel{?}{=} H_j$ Choose m_j $L_j = h(Nid_j \parallel n_i^*) \oplus m_j$ $SK_{ji} = h(F_j^* \| n_i^* \| m_j)$ $SV_j = h(Sk_{ji} \| T_1 \| T_2)$ $M_4 =< Pid_i^{\text{new}}, L_j, Sv_j, T_2 >$	
Check $T_{\text{fresh}} - T_2 \leq \Delta T$ Gateway GW		

$m_j^* = L_j \oplus h(Nid_j \parallel n_i)$ $Sk_{ij} = h(h(Id_i \parallel n_i)\|n_i\|$ $Sv_i = h(Sk_{ij}\|T_1\|T_2)$ $Sv_i \stackrel{?}{=} Sv_j$		

4.3 Login and authentication phase

MN_i and Sn_i mutually authenticate with the help of GW to create a session key. As shown in table 4 the login and authentication phases:

(a) Mn_i enters Id_i, Pw_i, and Bio_i, computes $PwB_i = h(Pw_i \parallel h(Bio_i))$ and $x_i^* = h(Id_i \parallel PwB_i)$, and checks whether x_i^* and x_i are the same. If they are not, Mn_i terminates this phase; otherwise, Mn_i random number produced and computes $A_i = y_i \oplus h(Id_i\|PwB_i\|r_{gu}), Un_i = h(A_i\|Pid_i\|n_i)$, and $Uz_i = n_i \oplus A_i$.

(b) Mn_i Sends the request,$M_1 =< Pid_i, Un_i, Uz_i, T_1 >$ to Sn_i.

(c) Sn_i computes checks T_1's freshness, generates n_j and computes T_1 freshness and calculates $x_j = y_j \oplus h(K_{gn} \parallel r_j||Nid_j)$, $A_j = h(x_j) \oplus n_j$and $B_j = h(x_j \parallel n_j)$.

(d) Sn_i Sends the message, $M_2 =< M_1, Nid_j, A_j, B_j >$ to GW.

(e) Upon reception of the message from Sn_i, GW calculates $x_j^* = h(Nid_j \parallel K_{gn}), n_j^* = h(x_j^*) \oplus A_j$, and $B_j^* = h(x_j^* \parallel n_j^*)$ and examine whether B_j^* and B_j are similar. If they are no identical, GW ends this phase; else, GW gets MN_i 's $< Id_i, r_d >$ by applying a key K_G to decode Pid_i and calculating $A_i^* = h(Id_i \parallel K_{gj}), n_i^* = Uz_i \oplus A_i^*$, and $UN_i^* = h(a_i^*\|Pid_i\|n_i^*)$ and checks whether UN_i^* and UN_i are similar. GW ends this phase if they aren't.; otherwise, GW generates r_D^{new} and computes $F_j = h(Id_i \parallel n_i^*), G_j = F_j \oplus x_j^*, R_{ij} = n_j^* \oplus n_i^*, H_j = h(x_j^*\|n_j^*\|n_i^* \parallel F_j)$, and$PID_i^{\text{new}} = E_{kg}(Id_i, r_d^{\text{new}})$.

(f) GW sends $M_3 =< Pid_i^{\text{new}}, G_j, R_{ij}, H_j >$ to Mn_i.

(g) Sn_i Computes $F_j^* = G_j \oplus X_j$, $n_i^* = R_{ij} \oplus n_j$ and $H_j^* = h(x_j\|n_j\|n_i^* \parallel F_j^*)$ and checks whether $H_j^* = H_j$. If N_j fails to do so, the phase terminates. Otherwise, N_j selects a random value m_j and calculates, $L_j = h(Nid_j \parallel n_i^*) \oplus m_j, Sk_{ji} = h(F_j^*\|n_i^*\|m_j)$ and $Sv_j = h(Sk_{ji}\|T_1\|T_2)$.

(h) N_j Sends $M_4 =< Pid_i^{\text{new}}, L_j, Sv_j, T_2 >$ to Mn_i.

(i) Mn_i Checks whether $T_{\text{fresh}} - T_2 \leq \Delta T$ and computes $m_j^* = L_j \oplus h(Nid_j \parallel n_i)$, $Sk_{ij} = h(h(I_i \parallel n_i)\|n_i\|m_j^*)$, and $Sv_i = h(Sk_{ij}\|T_1\|T_2)$. If Sv_i and Sv_j are the same, Mn_i and Sn_i produce the same session key successfully.

4.4 Password change phase

Mn_i updates their password on their mobile device during this phase. The details are as follows:

(a) Mn_i inputs $Id, Pw_i^{\text{dd}}, Pw_i^{\text{new}}$, and Bio_i, and computes $PWB_i^{\text{old}} = h(Pw_i||h(Bio_i))$ and $x_i^* = h(Id_i \parallel PwB_i^{\text{old}})$.

(b) Mn_i Checks whether x_i^* and x_i are the same. If they are not, Mn_i terminates this phase. Otherwise, Mn_i computes $A_i = y_i \oplus h(ID_i||PwB_i^{dd}||r_{gj}), PwB_i^{\text{new}} = h(PW_i^{\text{new}} \parallel H(Bio_i))$, $x_i^{\text{new}} = h(Id_i \parallel PwB_i^{\text{new}})$, and $y_i^{\text{new } i} = h(ID_i\|Pw^iB_i^{\text{new}}\|r_{gu}) \oplus A_i \oplus y_i$.

(c) Finally, Mn_i replaces the old x_i^{old} and y_i^{old} with x_i^{new} and y_i^{new}, respectively.

4.5 Revocation phase

Mn_i Incorporates a revocation technique that allows the secret parameters to be recovered by the mobile device.

(a) When a user wants to update or renew their secret parameter, they will input their previous identity Id_i^{old}, new identity Id_i^{new} new password Pw_i^{new} and Bio_i into their mobile device. Mn_i then computes $PwB_i^{\text{new}} = h(Pw_i^{\text{new}} \parallel H(Bio_i))$, $Mid_i^{\text{old}} = h(Id_i^{\text{old}} \parallel$

$H(Bio_i)\big)$, and $Mid_i^{\text{new}} = h\big(Id_i^{\text{new}} \parallel H(Bio_i)\big)$.

(b) Mn_i sends the revocation request message, $< Id_i^{\text{old}}, Id_i^{\text{new}}, Mid_i^{\text{old}}, Mid_i^{\text{new}}, PwB_i^{\text{new}} >$, to GW through a reliable channel.
(c) GW calculates $RID_i^{\text{old}} = E_{K_G}\big(Id_i^{\text{old}}\big)$ The system first verifies the identity of $Mn_i$and then searches for a pair. $(Rid_i^{\text{old}}, Mid_i^{\text{old}})$ to locate a registered user in the database. If the pairs (Rid_i, Mid_i) and $\big(RID_i^{\text{old}}, MID_i^{\text{old}}\big)$ are equal, GW produces new random numbers r_d^{new} and r_{gu}^{new}, computes $Pid_i^{\text{new}} =$

$E_{K_G}(Id_i, r_d^{\text{new}}), Rid_i^{\text{new}} = E_{kg}(Id_i^{\text{new}}),\ x_i^{\text{new}} = h(Id_i \parallel PwB_i^{\text{new}})$, and $y_i^{\text{new}} = h\big(Id_i||PwB_i^{\text{new}}||r_{gj}^{\text{new}}\big) \oplus h\big(K_{gu}||Id_i^{\text{new}}\big)$, and stores the new pair $(Rid_i^{\text{new}}, Mid_i^{\text{new}})$ in the database.

(d) GW sends $< Pid_i^{\text{new}}, x_i^{\text{new}}, y_i^{\text{new}}, r_{GJ}^{\text{new}} >$ to Mn_i.
(e) Mn_i the parameters obtained are saved in the mobile device.

5 BAN logic authentication proof

In this section, we utilized Burrows-Abadi-Needham (BAN) logic [51] to demonstrate that Mn_i and Sn_imutually authenticate each other correctly and that their distributed session key is up-to-date. BAN logic is a formal system that verifies the trustworthiness of every entity involved in an authentication protocol based on the source of communications, freshness, and reliability. Researchers also used extensively for evaluating the security of algorithms used in cryptography [51–52]. The following are the fundamental notations of BAN logic:
(1) $U \bowtie C$: U sees condition C.

(2) $U \mid\equiv C$: Condition C is U trust
(3) $\sharp(C)$: It creates an entirely fresh C.
(4) $U \mid\sim C$: U describes the circumstance C.
(5) $U \overset{K}{\leftrightarrow} S$: U and S share a secret key K.
(6) $U \Rightarrow C$: Condition C is handled by U.
(7) $(C_K$: C is encryption with key K.

(1) We use the five BAN logic principles stated below to show the mutual authentication of the proposed method. That U notices the C connected to K, that S shares the key K with S, and that U trusts S after bringing up C.

(2) Rule 2: The rule of once-verification: $\frac{U]=\#(C), U|=S\sim C}{U(\equiv)=C}$: If U believes in C's freshness and S believes in C, then U believes S believes in C.

(3) Rule 3: Trust rule: $\frac{U=C, U|=M}{A|=(C,M)}$: If User believes C and M, then (C, M) is also believed by U.

(4) Rule 4: Freshness-concatenation rule: $\frac{U_{\parallel}=\sharp(C)}{A_{\parallel}=+(C,M)}$: If U has faith in C's freshness, then U has jurisdiction over C's freshness as well. Likewise, if U has faith in S's confidence in condition C, then U also has faith in C. Through mutual authentication, we aim to establish a session key between Mn_i and n_j. To do this, we must complete the four tasks listed below.
(1) Goal 1: $MN_i \mid\equiv \big(Mn_i \overset{SK}{\leftrightarrow} Sn_i\big)$
(2) Goal 2: $Sn_i \mid\equiv \big(Mn_i \overset{SK}{\leftrightarrow} Sn_i\big)$
(3) Goal 3: $Mn_i|\equiv Sn_i| \equiv \big(Mn_i \overset{SK}{\hookrightarrow} Sn_i\big)$
(4) Goal 4: $Sn_i|\equiv Mn_i| \equiv \big(MN_i \overset{SK}{\leftrightarrow} Sn_i\big)$
The proposed scheme's four messages can be transformed into ideal forms.

(1) Using $M_1 =< Pid_i, Un_i, Uz_i, T_1 \gg,\ Mn_i \rightarrow Sn_i$: $Un_i = h(A_i \| Pid_i \| n_i), Uz_i = n_i \oplus A_i$. This has been lowered as $G_1 : (PID_i, A_i, T_1)_{n_i}$
(2) Using $M_2 =< M_1, Nid_j, A_j, B_j >, N_j \rightarrow GW$: $A_j = h\big(x_j\big) \oplus$

Sn_i, $B_j = h\big(x_j \parallel Sn_i\big)$. This is reduced as M_{SG}: $\big(M_1, Nid_j, Sn_i\big)x_j$
(3) Using $M_3 =< PID_i^{\text{new}}, G_j, R_{ij}, H_j >, GW_i \rightarrow Sn_i$: $G_j = F_j \oplus x_j^*,\ R_{ij} = n_j^* \oplus n_i^*,\ H_j = h\big(x_j^*||n_j^*\|n_i^*\|F_j\big)$. This is reduced as MSG $_3$: $\big(F_j, n_j, n_i, K_{gn}\big)x_j$
(4) Using $M_4 =< Pid_i^{new}, L_j, Sv_j, T_2 >, Sn_i \rightarrow Mn_i$: $L_j = h\big(Nid_j \parallel n_i^*\big) \oplus m_j t, Sv_j = h\big(SK_{ji}\|T_1\|T_2\big)$. This decreases as: MSG_4: $\big(\text{Pid}_i, \text{m}_j, \text{T}_1, T_2\big)_{m_i}$

We define the following assumptions to derive the proposed scheme's goals.

(1) A_1: $Mn_i \mid\equiv \sharp(T_1)$
(2) A_2: $Sn_i \mid\equiv \sharp(Sn_i)$
(3) A_3: $GW \mid\equiv \sharp(K_{CN})$
(4) A_4: $Sn_i \mid\equiv \pm(T_2)$
(5) A_5: $Sn_i \mid\equiv \big(Sn_i \overset{n_i}{\leftrightarrow} Mn_i\big)$
(6) A_6: $CW \mid\equiv \left(CW \overset{x_j}{\rightleftarrows} Sn_i\right)$
(7) A_7: $Sn_i \mid\equiv \big(Sn_i \overset{x_j}{\longrightarrow} CW\big)$
(8) A_{B}: $Mn_i \mid\equiv \big(Mn_i \overset{\pi_i}{\leftrightarrow} Sn_i\big)$
(9) A_g: $Mn_i \mid\equiv Sn_i \Rightarrow \big(Mn_i \overset{\mathcal{K}}{\leftrightarrow} Sn_i\big)$
(10) A_{10}: $Sn_i \mid\equiv Mn_i \Rightarrow \big(Mn_i \overset{\leftrightarrow}{\leftrightarrow} Sn_i\big)$

The following describes the primary proof that the proposed method is based on BAN logic rules, messages, and premises.

(1) Through MSG_1, we get V_1: $Sn_i \triangleleft (Pid_i, A_i, T_1)n_i$

(2) Through A_5 and Rule 1 , we get V_2: $Sn_i|\equiv Mn_i| \sim (Pid_i, A_i, T_1)_{m_i}$
(3) Through A_1 and Rule 4 , we get V_3: $Sn_i \mid\equiv \sharp(Pid_i, A_i, T_1)_{n_j}$
(4) Through V_1, V_2 and Rule 2, we get V_4: $Sn_i|\equiv Mn_i| \equiv (Pid_i, A_i, T_1)n_i$
(5) Through MSG_2, we get V_5 : CW $\triangleleft$ $(M_1, Nid_j, Sn_i)x_j$
(6) Using A_6 and Rule 1 , we get V_6: $GW|\equiv Sn_i| \sim (M_1, Nid_j, Sn_i)x_j$
(7) ThroughA_2 and Rule 4 , we get V_7: $GW \mid\equiv \sharp(M_1, Nid_j, sn_i)x.$
(8) Through V_5, V_6 and Rule 2, we get V_8: $GW|\equiv Sn_i| \equiv (M_1, Nid_j, Sn_i)x_j$

(9) Through MSG_3. we get V_g: $Sn_i \triangleleft (F_j, n_j, n_i, K_{cn})x_j$
(10) Through A_7 and Rule 1, we get V_{10}: $Sn_i| \equiv GW| \sim (F_j, Sn_i, n_i, K_{cn})x_1.$
(11) From A_3 and 4 , we get V_{11}: $Sn_i \mid\equiv \pm(F_j, Sn_i, n_i, K_{cn})x_j$
(12) From V_9, V_{10} and Rule 2, we get V_{12}: $Sn_i| \equiv dW| \equiv (F_j, Sn_i, n_i, K_{gn})x_j$
(13) Through MSG_4. We obtain V_{13}: $Mn_i \triangleleft (Pid_i, m_j, T_1, T_2)_{m_i}$ (14) Through A_8 and Rule 1 , we get V_{14}: $Mn_i|\equiv Sn_i| \sim (Pid_i, m_j, T_1, T_2)_{n_i}$
(15) Through A_4 and Rule 4 , We obtain V_{15}: $Mn_i \mid\equiv \sharp(Pid_i, m_j, T_1, T_2)_{m_i}$

(16) From $V_{13}.V_{14}$ and Rule 2 , we get V_{16}: $Mn_i \left|\equiv Sn_{i_j}\right| \equiv (Pid_i, m_j, T_1, T_2)_{n_i}$
(17) From V_{12}, V_{16}, and $SK = h(F_j \| n_i \| m_j)$. we get V_{17}: $Mn_i \mid\equiv \left(Mn_i \overset{SK}{\leftrightarrow} N_j\right)$ (Goal1)
(18) From V_4, V_8, and $SK = h(h(Id_i \| \mid n_i) \| n_i \| m_j)$, we get V_{18}: $Sn_i \mid\equiv \left(Mn_i \overset{\leftrightarrows}{\leftrightarrow} Sn_i\right)$ (Goal2)
(19) From A_9, V_{17} and Rule 5, we get V_{19}: $Mn_i|\equiv Sn_i| \equiv \left(Mn_i \overset{SK}{\leftrightarrow} Sn_i\right)$(Goal3)
(20) From A_{10}, V_{18} and Rule 5 , we get V_{20}: $Sn_i|\equiv Mn_i| \equiv$

$\left(Mn_i \overset{sK}{\leftrightarrow} Sn_i\right)$(Goal4)

We accomplished goals 1, 2, 3, and 4 are listed above. We see that Mn_i and Sn_i create a session key by means of safe mutual authentication.

```
Role alice (Ui, GWN. SNj: agent,
H: hash func.
SKuigwn: symmetric_key,
Snd, Rcv: channel(dy))
played by Ui
def= local State : nat,
IDi, IDsnj, K, PWi, Bi, T1, T2, T3: text,
Xs, EKi. Ki, Request, R, RPWi : text,
Gen, Rep: hash, func
const alice server_t1, server_bob_t2,
bob_ alice_t3, sub1, sub2, sub3, sub4 : protocol_id
init State := 0
transition
1. Stale = 0 /\ Rcv(start) =|>
% Registration phase
State' = 1 A K'= new()
/\ secret({PWi,Bi,K'),sub1.Ui)
/\ secret(EKi,sub2,{Ui,GWN})
/\ RPWi'= H(IDi.PWi.K')
% Ui sends login message to GWN securely
/\ Snd({IDi.RPWi'.EKi}.SKuigwn)
% Ui receives the smart card from GWN securely
2. State = 1 /\ Rcv ((H.Gen. Rep.H(xor(IDi.H(Xs)))_SKuigwn) =|>
% Login phase
State' := 2 /\ secret(Xs,sub3,GWN)
% Ui sends the login message to the GWN
/\ Snd(IDi.Request)
% Authentication and key agreement phase
% Ui reccives the message <R> from GWN
3. State = 2 /\ Rcv(R') =|>
State' = 3 /\ T1' := new()
% Ui sends the message <E_eki(R,T1,IDsnj)> to GWN
/\ Snd(R'.T1'.IDsnj}_ EKi)
% Ui has freshly generated the value T1 for GWN
/\ witness(Ui, GWN ,alice_server_ti, TI')
% Ui receives the message from sensor node SNj
2. State = 3 /\ Rcv (H {H(H (IDsnj.H (xor (IDi,H(Xs)))).
IDi.IDsnj.T1'.T3').T3')) =|>
% UI's acceptance of the value T3 generated for Ui by SNj
State':= 4 /\ request(SNj, Ui, bob_alice_t3, T3')
end role
role bob (Ui, GWN, SNj: agent,
H: hash_func,
SKuigwn: symmetric_key,
Snd, Rcv: channel(dy))
played_by SNj
def=
local State: nat,
IDi, IDsnj, K, PWi, Bi, TI, T2, T3: text,
Xs, EKi, Kj, Request, R, RPWi: text,
Gen, Rep: hash_func
const alice_server_t1, server_bob t2
```

```
bob_alice_t3, sub1, sub2, sub3, sub4: protocol_id
init State := 0
transition
% Authentication and key agreement phase
% Receive the message from the GWN
1. State = 0 /\ Rcv(IDi. (IDi.IDsnj.TI'.
T2'.H(IDsnj.H(xor(IDi,H(Xs))))] _ Kj)=|>
State': = 1 /\ T3' := new()
/\ secret((PWi,Bi,K),sub,Ui)
/\ secret(EKi,sub2,{Ui, GWN})
/\ secret(Xs,sub3,GWN)
/\ secret(Kj,sub4, {GWN,SNI})
% Send the message to Ui
/\ Snd(H(H(H (IDsnj.H(xor(IDi,H (Xs))))).
IDi.IDsnj,TI'.T3').T3'))
% SNj has freshly generated the value T3 for SNj
/\ witness(SNj.Ui,bob_alice_t3.T3')
% SNi's acceptance of the value T2 generated for SNj by
GWN
/\ request(GWN, SNj, server_bob_t2, T2')
end role
role server (Ui, GWN, SNj: agent,
H: hash_func,
SKuigwn: symmetric_key,
Snd, Rcv: channel(dy))
played_by GWN
def=
local State: nat,
IDi, IDsnj, K, PWi, Bi, T1, 12, T3: text,
Xs, EKi, KJ, Request, R, RAWi: text,
Gen, Rep: hash_func
const alice_server_t1, server_bob_t2,
bob_alice_t3, sub1, sub2, sub3, sub4 : protocol_id
init State := 0
transition
end role
% Registration phase
% GWN receives login message from UI securely
1. State = 0 /\ Rcv((IDi.H(IDi.PWi.K').EKi)_SKuigwn)=|>
State' := 1 /\ secret (PWi,Bi,K'},sub,Ui)
% GWN sends the smart card to Ui securely
/\ Snd({H.Gen.Rep.H(xor(IDi,H(Xs)))]_SKuigwn)
% Login phase: receive the login request message from Ui
2. State = 1 /\ Rcv(IDi.Request)=|>
State': = 2 /\ R' = new()
/\ secret(EKi,sub2, {Ui, GWN})
/\ secret(Xs,sub3,GWN)
/\ secret(Kj,sub4, {GWN,SNj})
% Authentication and key agreement phase
% GWN sends the message to Ui
/\ Snd(R')
end role
```

Figure 2: Role for user and gateway node

6 AVISPA tool simulation for formal security verification

This section presents the formal security verification of the AUSS scheme using the Automated Validation of Internet Security Protocols and Applications (AVISPA) tool. AVISPA has four back ends, but only the methods for OFMC back-end analysis are considered in this paper. An HLPSL is carried out to evaluate the security resistance to common attacks [39]. The CAS+ specifications are converted into HLPSL in AVISPA using the SPAN animator tool. In SPAN, the intruding mode creates a message sequence chart (MSC). Researchers and academics often use AVISPA or SPAN tools to confirm the security analysis of the design protocol [40].

7 Performance evaluation

In our evaluation we regarded the mobile node and gateway as computing environments in order to minimize the execution time of cryptographic procedures. For each cryptographic execution time, we referred to the results of experiments conducted on the sensor node by Abbasinezhad-Mood and Nikooghadam [50].

Our measurements, along with Abbasinezhad-Mood and Nikooghadam's [50] experiments, reveal the cryptographic times for the mobile node, sensor node, and gateway. We examined the 128-bit Advanced Encryption Standard (AES) algorithm (Ts), the 160-bit hash function (Th), and the 320-bit Elliptic Curve Cryptography (ECC) (Te). The XOR operation was not considered in our analysis due to its negligible impact. We measured the cryptographic execution times on two computing environments: a mobile node and a gateway, using data from Abbasinezhad-Mood and Nikooghadam [50]. The specifications are as follows:

1. Mobile Node: Galaxy Note 9 with an octa-core processor (2.7GHz + 1.7GHz), 8 GB of memory, running Android 9.0.
2. Sensor Node: LPC1768 device with an ARM Cortex-M3 processor (up to 100 MHz), 512 kB flash memory, and 64 kB SRAM.
3. Gateway: Intel(R) Pentium(R) processor G4600 (3.60 GHz), 8 GB of memory, running Windows 10.

The cryptographic times are as follows:

(1) Mobile node: $T_e \approx 29.48\mu s$, $T_s \approx 76.2\mu s$, and $T_h \approx 106.38\mu s$
(2) Sensor node: $T_e \approx 1263\mu s$ and $T_h \approx 15.5\mu s$
(3) Gateway: $T_e \approx 2226\mu s$, $T_s \approx 5.4097\mu s$, and $T_h \approx 4.9465\mu s$

The results show that the Turkanovic et al. scheme [25] has lower computational complexity but it is vulnerable to attacks, as noted by Farash et al. [26]. Our method has lower computational costs compared to those of Das et al. [42], Chang et al. [43], Yang et al. [44], and Wu et al. [46]. The system by Banerjee et al. [45] ranks second but lacks a revocation step. We also compared communication costs during the login and authentication phases. Our proposed scheme has a communication cost of 2112 bits, which is higher than Chang et al.'s approach but still more secure. Using hardware models relevant to real IoT environments, we found that our scheme's computation and transmission costs are slightly higher than some alternatives. Its reliance on XOR and hash operations makes it suitable for low-cost IoT devices while fulfilling all security requirements, thus making it applicable in various IoT scenarios. Figure 2 represents the role of user and gateway note. Figure 3 represents role of session and environment and figure 4 shows OMFC results. Table 5 represents the functionality and security comparison of our scheme with the existing scheme. Table 6 and figure 5 shows the comparison of communication cost of our scheme with the existing scheme. Table 7 and figure 6 represents the comparison of computation cost of our scheme with another scheme. Utilising the approach explained in [53,54], we assessed the communication expenses associated with the login and authentication phases. We presume that the lengths of the identity, timestamp, and random number values are 128, 32, and 64 bits, respectively. The symmetric key encryption, elliptic multiplication operation, and hash function generate 256, 360, and 160 bits, respectively.

```
role session(Ui, GWN,SNj: agent,
% H is hash function
H: hash_func,
SKuigwn: symmetric_key)
def=
local US, UR, SS, SR, VS, VR: channel (dy)
composition
alice(Ui, GWN, SNj, H, SKuigwn, US, UR)
/\ server(Ui, GWN, SNj, H, SKuigwn, SS, SR)
/\ bob(Ui, GWN, SNj, H, SKuigwn, VS, VR)
end role
role environment)
def=
const ui, gwn, snj: agent,
h, gen, rep: hash_func,
skuigwn: symmetric_key,
idi, idsnj, t1, t2, t3 : text,
alice_server_tl, server_bob_t2,
bob_alice_13, sub1, sub2,
sub3, sub4 : protocol_id
intruder_knowledge = (idi,h,gen,rep,t3 )
composition
session (ui, gwn, snj, h, skuigwn)
session(ui, gwn, snj, h, skuigwn)
/\ session(ui, gwn, snj, h, skuigwn)
end role
```

Figure 3: Role for session and environment

```
% OFMC
% Version of 2006/02/13
SUMMARY
SAFE
DETAILS
BOUNDED_NUMBER_OF_SESSIONS
PROTOCOL
/home/span/span/testsuite/results/AUSS.if
GOAL
as specified
BACKEND
OFMC
COMMENTS
STATISTICS
parseTime: 0.00s
searchTime: 0.14s
visitedNodes: 16 nodes
depth: 4 plies
```

Figure 4: OFMC output

Table 5: Comparison functionality and security attribute

ATTACKS	UAA	UUA	SMDA	MA	SKAA	UIA	RA	UVA	SVA	PIA	PCA	FSA	SNIA	RPA
[7]	✓	×	×	✓	✓	×	×	✓	✓	✓	✓	✓	✓	×
[25]	✓	×	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×
[42]	✓	×	✓	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	×
[43]	✓	×	×	✓	×	✓	✓	×	✓	✓	✓	×	✓	×
[44]	×	×	×	✓	-	✓	✓	×	×	✓	✓	✓	✓	×
[45]	✓	×	✓	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	×
[46]	✓	×	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×
AUSS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	×

Table 6: Comparison of the communication cost

Scheme	[7]	[25]	[42]	[43]	[44]	[45]	[46]	AUSS
MN(User)	832	672	672	512	864	800	864	480
SN	1760	1440	1184	1024	1728	2080	1408	1472
GW	576	576	512	512	1024	320	320	640
Messages	4	4	4	4	4	4	4	4
Total(bits)	2880	2688	2368	2048	3712	3200	2592	2112

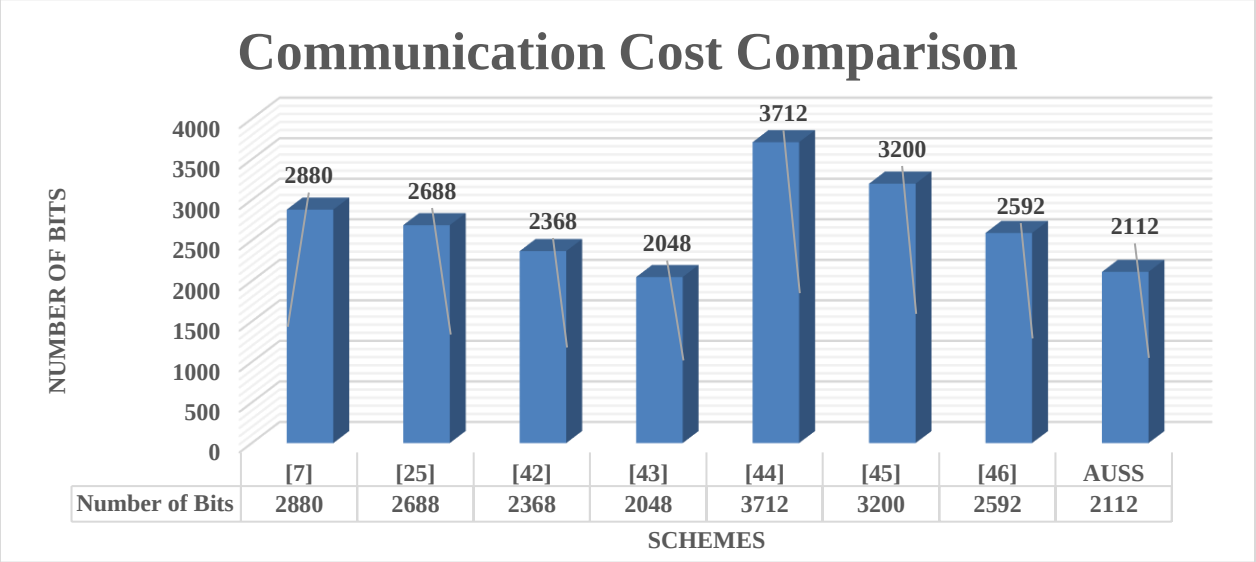

Figure 5: Comparison of Communication cost

Table 7: Comparison of computation

Scheme	[7]	[25]	[42]	[43]	[44]	[45]	[46]	AUSS
MN(User)	$9T_h$	$7T_h$	$8T_h + 2T_e$	$7T_h + 2T_e$	$16T_h$	$9T_h$	$11T_h$	$9T_h$
SN	$6T_h$	$5T_h$	$9T_h + 1T_e$	$5T_h + 2T_e$	$16T_h$	$6T_h$	$5T_h$	$7T_h$
GW	$7T_h$	$7T_h$	$10T_h$	$9T_h$	$20T_h$	$6T_h$	$15T_h$	$8T_h + 2T_s$
Time	$\approx 1085\mu s$	$\approx 856\mu s$	$\approx 1323\mu s$	$\approx 2585\mu s$	$\approx 2049\mu s$	$\approx 1080\mu s$	$\approx 1321\mu s$	$\approx 1115\mu s$

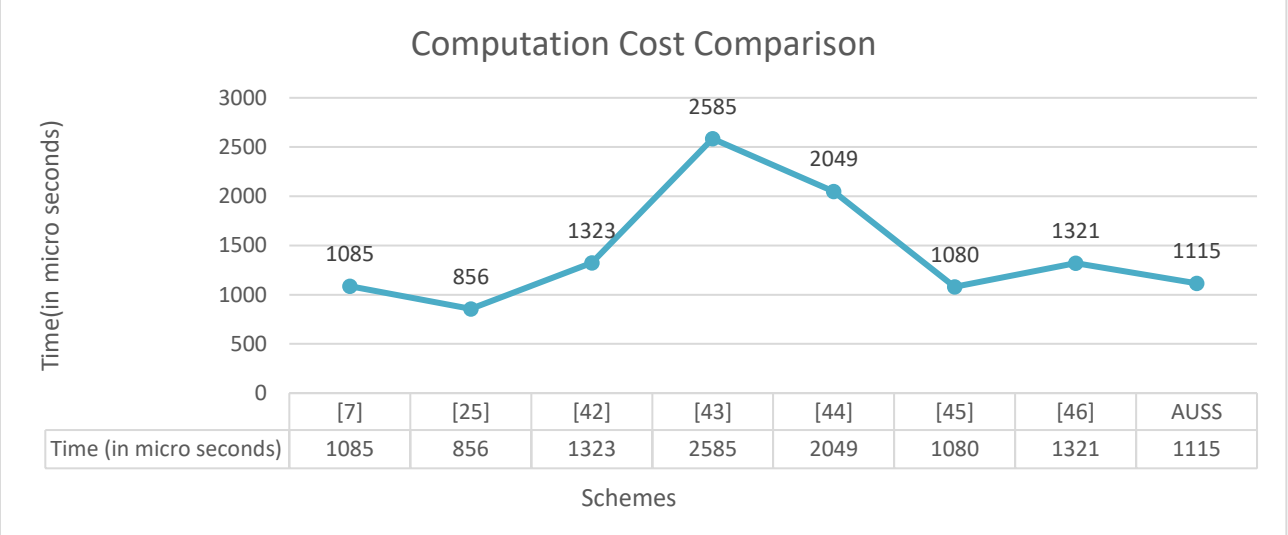

Figure 6: Comparison of computation cost

8 Conclusion

Our research paper presents a significant breakthrough in user authentication techniques. We identified several security flaws in the user authentication method developed by Dhillon and Kalra. In response to these issues, we propose an improved approach that enhances security considerably. To evaluate the effectiveness of our proposed scheme, we utilized BAN logic and conducted both formal and informal security assessments. Our analysis indicates that the proposed scheme meets all security standards and is resistant to

various known threats. Additionally, we performed a comparative performance analysis against other relevant schemes, considering the hardware specifications of mobile and sensor devices in real Internet of Things (IoT) environments. The findings reveal that our proposed method is compatible with low-cost IoT devices. In summary, the proposed user authentication method offers a practical and secure solution for IoT applications.

Conflict of interest

The author has declared no conflicts of interest.

Financial disclosure

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Ensemble-Based Network Anomaly Detection Using RFE and Information Gain for Optimized Feature Selection

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Intrusion Detection Systems (IDSs) play a significant role in reducing dynamic cyber threats. However, current machine learning-centric IDSs are not without issues, as they may have a high false positive rate and suboptimal feature selection, resulting in a low detection rate. This paper proposes an ensemble IDS architecture that utilizes RFE and IG for feature selection, aiming to enhance anomaly detection performance and reduce computational intensity. We begin with a preprocessing pipeline that includes data cleaning, one-hot encoding of categorical features, and normalization to scale the features. The most discriminative attributes are selected to minimize redundancy. Then, the selected feature subset is fed to build a set of ensemble classifiers, including Random Forest, XGBoost, Extra Trees, and a weighted Voting Classifier. Extensive experimental results on the CIC-IDS2017 datasets demonstrate that the proposed ensemble-level approach outperforms in all aspects, achieving 97.5% accuracy, 97.2% precision, 97.8% recall, and 97.5% F1-score. Overall, the ensemble model exhibits an improvement in terms of recall and hence robustness compared to the two baseline classifiers, namely the standalone Random Forest (recall: 96.5%) and XGBoost (recall: 97.3%). We also conducted an ablation study that confirms the effectiveness of RFE and Information Gain by comparing settings with and without feature selection. These findings indicate that the proposed IDS architecture can be feasibly and scalably implemented for real-time network anomaly detection. Adaptive feature selection and deployment in a streaming setting could be investigated to enhance its resistance to novel attacks in the future.

Povzetek: Sistem uvaja hibridni pristop za odkrivanje omrežnih napadov. S kombinacijo RFE in Information Gain izbere ključne značilke, nato jih združi z ansambelskim učenjem (Random Forest, XGBoost, Voting). Rezultat je večja točnost in manj lažnih alarmov; metoda izboljša odzivnost IDS in omogoča skalabilno zaznavanje napadov v realnem času.

1 Introduction

In modern cybersecurity, intrusion detection systems (IDS) are key to monitoring network traffic and detecting malicious actions. Signature-based and anomaly-based detection techniques in traditional intrusion detection systems (IDS) cannot cope with the rapidly evolving cyber threats. Due to constant updates, signal-based approaches are traditionally ineffective against zero-day attacks, while anomaly-based solutions experience high false positive rates. Machine learning (ML)-based methods have overcome some of these limitations by incorporating automatic feature selection and anomaly classification capabilities into Intrusion Detection Systems (IDSs) [6, 7]. Ensemble learning techniques, such as Bagging, Boosting, and Random Forest, have further enhanced classification performance [8]. Nonetheless, optimizing feature selection, enhancing classification accuracy, and adapting to new attack patterns are still challenging.

Several previous studies have explored feature selection and ensemble learning to improve.

Intrusion detection performance. For example, Chohra et al. [1] employed PSO as a search function (SF) technique to enhance the accuracy of detection. However, it is not the exact grid search as ours because it is non-deterministic and non-interpretable. In contrast, our criterion is a deterministic and interpretable combination of RFE (Recursive Feature Elimination) and Information Gain, which addresses redundancy and improves generalization. Our proposed approach is designed to be used with ensemble tree-based classifiers, which provide high accuracy and are reasonably interpretable. Abbas et al. [2] investigated the best model between ensemble-based and single classifiers, demonstrating that ensemble-based intrusion detection models could achieve a better detection rate. Nevertheless, it has been found that these approaches have several drawbacks, including suboptimal feature selection, a lack of multiple classifiers, and ineffectiveness in detecting imbalanced attack classes. Additionally, most

approaches are unable to adapt to the dynamic nature of cyber threats. Therefore, there is a need for an automated IDS framework that offers high adaptability, accuracy, scalability, and sustainable performance. To address these gaps, this study presents an optimized hybrid intrusion detection framework that leverages Recursive Feature Elimination (RFE) and Information Gain in conjunction with ensemble learning models to enhance classification accuracy, precision, recall, and F1-score. Compared to previous methods, our proposed model can automatically eliminate irrelevant features, reduce computational overhead, and improve detection performance. Moreover, it increases the classification rate of both seen and unseen attacks using XGBoost, Random Forest, and an Ensemble Voting Classifier, which yields better results than classical one-class classifier approaches.

In this study, the novelty lies in the utilization of a combination of RFE and Information Gain for feature selection, resulting in a detailed and refined dataset for classification. This algorithm combines the outputs of multiple models, thus increasing overall detection accuracy, minimizing false alerts, and improving model stability and reliability. In addition, this study conducts a comprehensive ablation analysis to demonstrate the impact of feature selection on model performance and to gain a deeper understanding of how feature selection enhances IDS efficiency.

To set the research direction, this study aims to evaluate whether ensemble classifiers based on RFE, IG, or SFFS, or IG Feature Score as feature selection techniques can significantly enhance IDS classifiers compared to single classifiers. The central hypothesis is that by utilizing sophisticated feature selection techniques in conjunction with ensemble learning, our system can achieve improved accuracy, reduced false positives, and increased generality in detecting new cyber threats. The specific contributions are as follows: for the first time, we construct a stable data pipeline, propose a hybrid feature selection method that retains high-dimensional features with discriminative value, and compare multiple ensemble classifiers (i.e., Random Forest, XGBoost, Extra Trees, and Voting Classifier) in the optimized feature space. We conduct thorough experimentation to justify further the proposed framework, including comparisons with state-of-the-art models, ablation analyses, and investigations into interpretability. This organized research framework ensures that the solution not only fills the gap in feature selection and detection accuracy but also provides a scalable and deployable model for modern network security systems.

Our primary research contributions are as follows: opting for an optimized IDS framework based on ensemble learning, integrating feature selection techniques to enhance model performance, and conducting an extensive analysis of the model against state-of-the-art approaches. A comprehensive performance comparison is also included in this study, which validates the real-world applicability of the proposed model for cybersecurity. The paper is organized as follows: Section 2 presents an extensive literature survey on existing intrusion detection systems (IDS) techniques, their weaknesses, and recent trends in feature selection and ensemble techniques. The proposed methodology is described in Section 3, which includes feature selection strategies and the ensemble-based classification approach. Section 4 presents experimental results using our model, including ablation studies and comparisons with the state-of-the-art. In Section 5, we present the study's findings, implications, and contributions, as well as its limitations. The final section, Section 6, concludes the work by presenting key findings and recommendations to enhance the effectiveness of IDS.

2 Related work

Recent research on intrusion detection systems explores various machine learning techniques, focusing on feature selection and ensemble learning to enhance network anomaly detection. Chohra et al. [1] developed a feature selection approach based on swarm intelligence, which demonstrated good performance across various datasets. However, the scalability still has to be improved. Velasquez et al. [2] developed a hybrid ensemble model that performed well but required further testing in various settings for real-time anomaly detection in industrial systems. Khan and Sayyid et al. [3] investigate different machine learning models for predicting thyroid disorders in diabetic patients. Random Forest and SVM showed high predictive performance. The proposed approach emphasizes the importance of disease-specific cause selection and dataset balancing in improving the performance of machine learning for accurate clinical decision-making. Aliyeva et al. [4] investigated the use of XGBoost to increase efficiency by automating cybercrime detection; however, difficulties arise with human procedures and algorithmic constraints. Abbas et al. [5] proposed an ensemble intrusion detection model that combines decision trees, naive Bayes, and logistic regression. It demonstrated increased accuracy, but further improvements are needed to keep pace with the ever-evolving nature of cyber threats.

Hossain and Islam [6] presented an ensemble-based intrusion detection model with good accuracy utilizing various methods; nevertheless, further work is required to improve generalizability across different datasets. Thockchom et al. [7] improved performance by developing an ensemble learning model for intrusion detection that utilizes lightweight classifiers; however, difficulties with misclassification and dataset diversity should be addressed in future research. Eddine et al. [8] developed a feature-engineered machine learning-based intrusion detection model for the Industrial Internet of Things (IIoT), achieving high accuracy. However, future research should focus on possible security flaws. Golchha et al. [9] proposed a framework for voting-based ensemble learning that utilizes CatBoost, HGB, and RF to detect IIoT cyberattacks with high accuracy. Future research should focus on more general attacks and practical uses.

Adeshina et al. [10] compare linear and logistic regression models for disease prediction. The process consists of three steps: preprocessing, a test for multicollinearity, and statistical validation. The results suggest that logistic regression is superior to other methods in predicting trends or glitches in binary classification problems, due to its proper handling of categorical disease outcomes.

Hooshmand et al. [11] proposed a hybrid sampling approach (SKM) to detect network anomalies, thereby increasing the detection rates of the minority class. Subsequent research should delve deeper into optimization and assess its use with a broader range of datasets. Ahmed et al. [12] developed the Deep Ensemble Learning Model (DELM) to detect abnormalities in network data and utilize Adaptive Feature Aggregation to enhance flexibility. Enhancing real-time detection capabilities and testing against various attack types should be the main priorities of future development. Lai et al. [13] developed an ensemble learning system to detect anomalies in IoT cybersecurity; however, it struggles with diverse data. More comprehensive applications could be investigated in future research. Allafi et al. [14] created the ensemble learning-based AOAEL-CDC approach for IoT cybersecurity; however, it has issues with traditional IDS. Subsequent research might improve methods of detection. Lin et al. [15] encountered difficulties with offline modifications and created an ensemble machine learning network intrusion detection system (ML NIDS) based on a hypergraph for real-time port scan detection. More research might enhance adaptability even more.

Kunhare et al. [16] increased accuracy and decreased false alarms using a random forest approach for feature selection in IDS. Other optimization strategies may be explored in future research. Almasoudy et al. [17] proposed a feature selection approach for IDS based on Differential Evolution, which improved detection rates but encountered complexity issues. Accuracy may be further refined in future studies. Li et al. [18] presented AE-IDS, a deep learning technique that shortens training times while improving intrusion detection accuracy. Reliance on labeled datasets is one of the limitations; this may be addressed in further study. Taoussi et al. [19] describe a hybrid model for depression detection, which utilizes SMOTE to address class imbalance, RoBERTa for extracting deep contextual embeddings, and CNN-LSTM for temporal classification. The proposed end-to-end model achieves higher accuracy and robustness compared to the state-of-the-art models, especially on the imbalanced mental health dataset. Prasad et al. [20] developed a hybrid feature selection strategy to enhance intrusion detection using Bayes' theorem and Rough Set theory. Potential biases in the dataset are among the limitations; more research may improve scalability.

Stiawan et al. [21] developed an enhanced ensemble IDS incorporating six feature selection techniques to improve detection precision. A reliance on specific datasets is one limitation; larger datasets and methodologies may be explored in future studies. Sarvari et al. [22] developed a Cuckoo Fuzzy Mutation method for IDS feature selection, which improved performance but had limitations with specific datasets. Future research could examine more datasets and algorithms. Kunal and Dua [23] suggested an ensemble classifier with reasonable accuracy for IDS that used ranker-based attribute assessment. One of its limitations is reliance on the NSL-KDD dataset; other datasets and further optimizations can be explored in subsequent studies. Velliangiri and Karthikeyan [24] created a hybrid intrusion detection optimization technique that improves feature relevance. One of its limitations is reliance on the NSL-KDD dataset; further study could explore other datasets and optimization strategies. Khammassi and Krichen et al. [25] proposed a multi-objective feature selection technique that utilizes logistic regression and NSGA-II for intrusion detection, thereby enhancing classification accuracy. One limitation is that performance varies across different datasets; further research may investigate other classifiers and optimization strategies to address this variation.

Injadat et al. [26] proposed an enhanced multi-stage ML-based NIDS architecture that reduces training size and increases detection accuracy. Dataset reliance is one of the limitations; future research may focus on the applicability of more extensive datasets and advanced optimization strategies. Hmouda and Li [27] suggested an intrusion detection system based on entropy that selects features using the V-measure to improve classification accuracy. The dataset's specificity is one of its limitations; further study may explore other datasets and feature selection techniques to enhance its applicability. Leevy et al. [28] highlighted performance consequences and recommended future improvements after analyzing feature selection and classifier comparison on CSE-CIC-IDS2018. Alzahrani et al. [29] enhanced intrusion detection by using SSPLR and SVM, highlighting the drawbacks of SVM and emphasizing the advantages of SSPLR for feature selection; further study is recommended. Ghasemi et al. [30] utilized a Kernel Extreme Learning Machine and Genetic Algorithms to select features in IDS with high accuracy; further improvements are suggested.

Table 1: Summary of literature findings

Reference	Approach	Technique	Algorithm	Dataset	Limitations / Future Scope
[5]	Machine Learning and Deep Learning	DL techniques	ML algorithms	CICIDS2017 dataset	Future work will extend the ensemble model with deep learning to improve accuracy.
[7]	Machine Learning and Deep Learning	Gaussian Naive Bayes, Logistic Regression, and Decision Tree	ML algorithm	KDD Cup 1999, UNSW-NB15, and CIC-IDS2017	Future research will address class imbalance using synthetic oversampling and cost-sensitive models.
[11]	Machine Learning	SMOTE	XGBoost and K-Means Clustering (SKM)	NSL-KDD and UNSW-NB15 datasets	Improvements will focus on reducing false alarms and enhancing the system's explainability.
[14]	Machine Learning and Deep Learning	AOAEL-CDC technique	Artificial Orca Algorithm	UNSW-NB15 dataset	Future work will explore unsupervised and reinforcement learning for better anomaly detection.
[17]	Extreme Learning Machine	ANN and FS+SVM	DE algorithm	NSL-KDD dataset	Future testing on live networks with more complex classifiers to improve U2R attack detection.
[21]	Machine Learning	Bayesian Network, Naïve Bayes, Decision Tree: J48 and SOM	J48 algorithm	ITD-UTM dataset	Plans to develop an ensemble IDS with improved feature selection and multiple datasets.
[24]	Machine Learning	Naïve Bayes, AABC, APSO, and SVM	Naïve Bayes, Genetic Algorithm	NSL-KDD dataset	Future work will reduce feature subsets while maximizing detection rate using optimization techniques.
[25]	NSGA2-LR Wrapper Approach	IDS methods	NSGA-II	NSL-KDD, UNSW-NB15, CIC-IDS2017	Future research will prioritize the detection rate over accuracy to handle unbalanced data better.
[34]	Machine Learning	ML techniques	SVM and ANN algorithms	AWID dataset	Future enhancements will integrate deep learning for improved classification accuracy.
[38]	Machine Learning	Tabu Search - Random Forest (TS-RF)	ML algorithm	UNSW-NB15 dataset	Future work will address class imbalance issues to reduce false positives and misclassifications.

Karatas et al. [31] created six IDSs based on machine learning that improve the detection of infrequent intrusions by addressing imbalances using SMOTE and an updated dataset. Prasad et al. [32] presented an unsupervised feature selection and clustering technique for IDS that addresses the limitations of labeled data while increasing accuracy and efficiency. Kilincer et al. [33] analyzed AI-powered IDS development, assessed datasets, applied normalization, and categorized data, emphasizing effective results. The heterogeneity of the dataset is one limitation; more sophisticated AI approaches may be explored in future studies. Zhu and Guo [34] propose a machine learning-based damage identification system to detect damage in prestressed concrete elements using piezoelectric sensor data. They also employ an optimal feature learning algorithm to achieve better diagnostic accuracy. The numerical results demonstrate the feasibility of using 12 sensors for fault detection and the optimization of structural health monitoring systems in civil infrastructure applications. Halim et al. [35] created a 99.80% accurate improved GA-based feature selection technique for network security. The dataset's breadth is one of its limitations; more varied datasets may be explored in further study.

Table 2: Datasets used in prior works

Dataset	**References**
NSLKDDdataset	[1], [4], [7], [11], [16], [17], [19], [22], [23], [24], [25], [29], [30], [32], [37], [40]
UNSW-NB15 dataset	[1], [7], [11], [14], [25], [26], [33], [35], [36], [38]
BlogCatalog dataset	[3]
CICIDS2017 dataset	[5], [7], [9], [15], [20], [25], [26], [27], [32], [39]
NF-UQ-NIDS dataset	[6]
CSE–CIC–IDS2018 dataset	[6], [18], [28], [31], [33]
Bot-IoT dataset	[8], [35]
NF-UNSW-NB15-v2 dataset	[8]
CCF (Credit Card Fraud) dataset	[10]
CCDP (Credit Card Default Payment) dataset	[10]
AWID dataset	[19], [34]
ITD-UTM dataset	[21]
Wormhole dataset	[32]
ISCX-2012 dataset	[33]
CIDDS-001 data set	[33]
CIRA-CIC-DOHBrw- 2020, dataset	[35]

Ngo et al. [36] highlighted performance data and recommendations while contrasting feature extraction and selection techniques for IoT intrusion detection. One limitation is the specificity of the dataset; more significant scenarios could be covered in further work. Mauro et al. [37] evaluated current datasets and methodologies for feature selection in network intrusion detection. Issues with feature correlation are among the limitations; real-time applications may be explored in subsequent studies. Nazir et al. [38] provided TS-RF, a wrapper-based feature selection technique, to improve NIDS performance. One of its limitations is the reliance on specific datasets; broader applications could be explored in future research.

Table 3: Comparative summary of related intrusion detection methods

Reference	**Methodology**	**Feature Selection**	**Model(s) Used**	**Dataset**	**Accuracy (%)**	**Limitations**
[1] Chohra et al. (2022)	Ensemble + PSO	PSO	RF, SVM	CIC-IDS2017	94.5	Static FS lacks adaptability to evolving attacks
[6] Hossain & Islam (2023)	Supervised ML	RFE	XGBoost, ET	UNSW-NB15	95.8	Single dataset tested, lacks explainability
[11] Hooshmand et al.	XAI + ML	SHAP	XGBoost, ANN	UNSW-NB15	96.1	Interpretability was added, but it lacks ensem

(2024)						ble diversity
[12] Ahmed et al. (2024)	Adaptive FS	Feature Aggregation	RF, SVM	CIC-IDS2017	96.4	Limited scalability, dataset-specific tuning
[15] Lin et al. (2024)	GNN-based	Graph-Based FS	GNN	CIC-IDS2017	96.8	High memory overhead, complex deployment
Proposed Work	Hybrid Ensemble	RFE + IG	XGBoost, RF, Voting	CIC-IDS2017	**97.5**	Single dataset; static FS – future work on adaptivity

Saber et al. [39] presented a novel intrusion prevention system (IPS) that enhances detection rates and reduces false alarms by utilizing ensemble learning and meta-classifier feature selection. One of the limitations is computational complexity; future efforts may focus on optimizing and scaling up the approach to improve its efficiency. Semenets et al. [40] enhanced classifier performance by implementing a multi-measure feature selection approach for intrusion detection. Data variability is one of the limitations; future studies can concentrate on improving the algorithm. Table 1 summarizes the literature findings, while Table 2 presents the widely used datasets in prior works. Table 3 provides a Comparative analysis of existing IDS approaches, highlighting models, feature selection strategies, datasets, accuracy, and key limitations addressed. Although many swarm intelligence, SHAP-based inter-probability, and graph-based deep learning techniques have recently been considered in IDS modeling, these methods are not generalizable across datasets, require high computational effort, or fail to realize the synergy of feature selection and ensemble classification. For instance, SHAP-based models enhance interpretability, but they introduce a complex structure that is not suitable for real-time deployment. PSO and other heuristic techniques are for selection purposes only, are static, and do not apply to multiple classifier systems more effectively. To summarize, our framework addresses these gaps by integrating RFE and Information Gain methods to learn features and utilizing an ensemble voting scheme to enhance robustness, accuracy, and generalization on the CIC-IDS2017 dataset. In contrast to the above models, the proposed architecture is both computationally efficient and deployable.

3 Proposed framework

The framework of the proposed network anomaly detection system is based on a machine learning framework, which enhances detection performance by optimizing data preprocessing and feature selection techniques [8], as illustrated in Fig. 1. It begins with the CIC-IDS2017 dataset, comprising labeled network traffic data that encompasses both standard and attack samples. We then perform various preprocessing steps on the dataset, including data cleaning for missing values and duplicates, normalization to standardize the scales of features, and encoding to transform categorical features into numerical representations that machine learning models can utilize. The preprocessing is preceded by our proposed feature selection mechanism that selects only the most significant features to create a low-dimensional intrusion detection model on the reduced dataset. This methodology combines Recursive Feature Elimination (RFE), a process that successively removes features that contribute the least to the model's prediction power. Moreover, information gain is used to calculate the relevance of each feature in distinguishing between typical and attack instances, and only the top attributes are used to train the model.

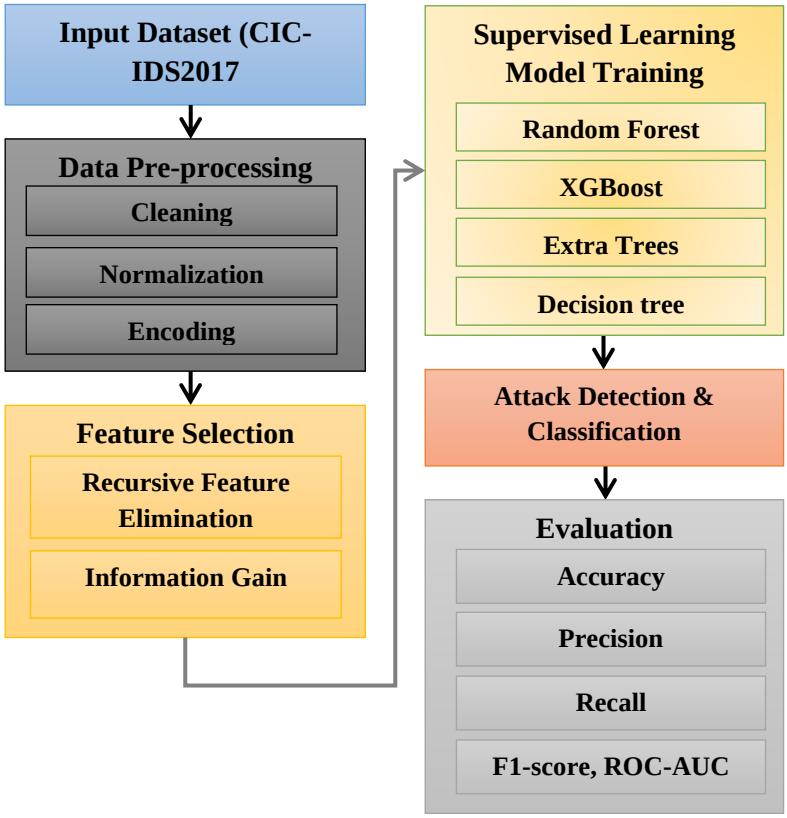

Figure 1: Proposed framework for network anomaly detection using optimized feature selection and ensemble learning

After we finish the feature selection, we train a set of supervised learning models with the reduced data. The framework utilizes ensemble classifiers, including Random Forest, XGBoost, Extra Trees, and Decision Tree models. The models used in this approach are trained on historical data of the attacks and the generalization of that data, allowing the models to classify the data and identify whether the given data contains malicious activity. By leveraging the multiple perspectives of data, the ensemble approach increases robustness and reduces biases among individual classifiers. The generated models are then used to detect and classify attacks by categorizing the incoming network traffic into regular or specific classes of attack. To determine the number of Genuine and malicious while keeping the False alarm rate as low as possible, we evaluate using key classification metrics such as accuracy, Precision, Recall, F1-score, and ROC-AUC. Figure 1: Proposed Methodology for Improving Accuracy and Stability of Network Anomaly Detection by Optimizing Preprocessing, Feature Selection, and Classification Based on Ensemble

3.1 Data preprocessing

As illustrated in Figure 2, the data preprocessing phase ensures the essential quality and consistency of network traffic data before feature selection and model training. Features: The raw dataset contains missing values, duplicated entries, and categorical attributes that need to be converted into a form better suited for machine learning applications. Step 1 — Data Cleaning. Data Cleaning is the first step in preprocessing, where we address missing values by either taking the average or removing records containing missing values, ensuring there are no duplicate records. This ensures that the model will not be negatively affected by any inconsistency. Then, feature encoding is performed to convert the categorical variables into numerical variables. The dataset ultimately consists of symbolic attributes, such as protocol type, service, and attack, which require encoding. In binary classification, we transform the results using label encoding. In contrast, we use one-hot encoding on the remaining dataset columns to obtain a less redundant numerical representation, which is more suitable for machine learning models.

Normalization is used to scale all numerical features within a standardization range, ensuring that larger numerical values do not disproportionately influence the model's assignment of importance to these features. There are other scaling techniques, such as min-max scaling, in which feature values are scaled between 0 and 1, and standardization, in which the mean is set to 0 and the variance is set to 1. Step 3 — This step facilitates the convergence of the model and reduces bias due to varying feature magnitudes, thereby improving classification performance. After preprocessing, the dataset is split into training and testing datasets for an effective model evaluation process. The data is divided into an 80:20 ratio, where 80% of the data is used for training the model, and 20% of the data is reserved for testing. By splitting the data into two segments, one for training and the other for validation, the developed model observes generalization towards data that it has not seen before, thereby avoiding overfitting. The environmental preprocessing pipeline

enhances data quality and feature selection, thereby improving the performance of machine learning models in detecting network anomalies.

The proposed framework was implemented using Python 3.9, leveraging Pandas for data preprocessing and feature handling, and Scikit-learn for employing Information Gain, Recursive Feature Elimination (RFE), and classic ensemble classifiers, including Random Forest, Extra Trees, and Decision Tree. Even with TensorFlow in the environment, TensorFlow was not utilized in the final model, as the study focused on tree-based classifiers rather than neural networks.

3.2 Feature engineering

As shown in Figure 2, which represents Feature selection, this is one of the basic steps we need to follow to reduce dimensionality and retain the most significant attributes, thereby achieving optimal performance from the model. As you can see, the dataset comprises many features, some of which may be repetitive or irrelevant in detecting an intrusion. Feature selection enables efficient computation, reduces the likelihood of overfitting by selecting relevant features, and enhances classification accuracy. RFE and information gain also retain the features used in the method. Recursive Feature Elimination (RFE) is an iterative method that repeatedly constructs a model and removes the weakest features until the specified number of features is reached. It starts by fitting a baseline model to all provided features, ranking them by importance, and then recursively dropping the least important features. The above process continues until v. RFE reduces the redundancy of features, leading to a better understanding of the model and higher efficiency without sacrificing detection accuracy.

The proposed feature selection engineering utilizes Information Gain and Recursive Feature Elimination (RFE) to reduce the dimensionality of the input space before classification. For example, Information Gain ranks features according to how well they minimize entropy concerning class labels and filters out the irrelevant features, i.e. These features give relatively little to class separation. On the other hand, an RFE recursively fits models and trims the model by removing the least essential features from the input set of features. Combined, these techniques help reduce dimension and improve computation efficiency, while still achieving higher classification accuracy, precision, recall, and F1-score than the others.

RFE specifically reduces redundancy and weak influence among features, leading to a more compact and informative subset. When used in conjunction with Information Gain, the process ensures that only the most relevant and non-redundant features are retained for training, improving both computational efficiency and model generalization.

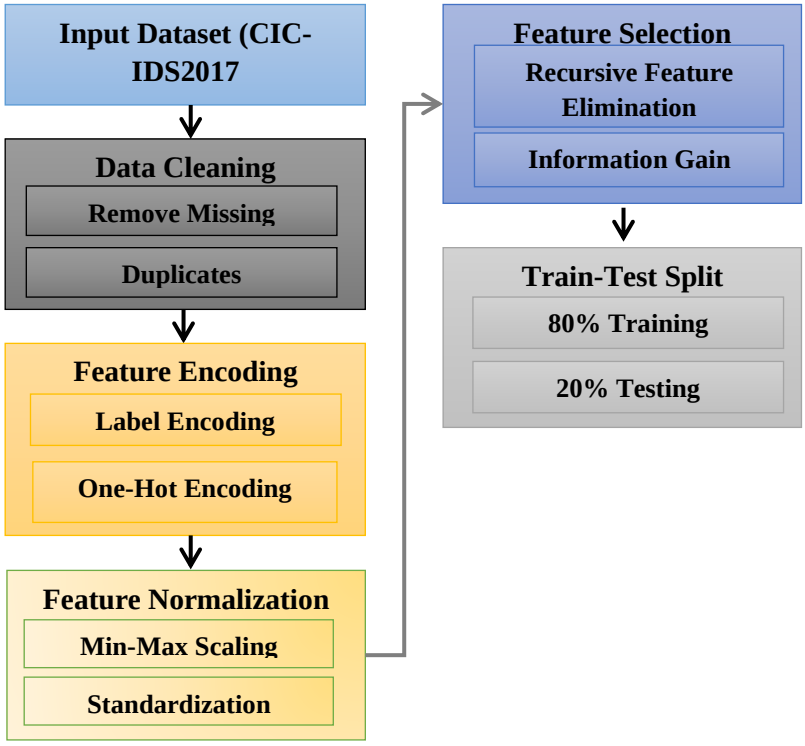

Figure 2: Illustrates data preprocessing and feature selection mechanisms

Information Gain is another feature selection technique that measures the contribution of individual features in separating the response classes (normal v/s attack). It calculates the change in entropy when using that feature to classify the target variable, thereby measuring the amount of information a given feature provides about the target

variable. The intuition behind high information gain is that converting a feature into a decision is preferred, as it has a positive impact on decision-making. This approach ensures the preservation of only the most discriminative features, thereby enhancing the model's ability to distinguish between various types of attacks. Recursive Feature Elimination along with Information Gain to provide optimal predictive power with the least complexity. This step not only simplifies the training process but also decreases the computational burden and improves the generalization capability of the proposed framework for intrusion detection.

The resultant set of features selected after performing Information Gain (IG) and Recursive Feature Elimination (RFE) is passed as input to the classification models in this work. These features are then input into a set of supervised ensemble-based classifiers, such as Random Forest, XGBoost, Extra Trees, and Decision Tree models. These classifiers are independent and make predictions that are combined by weighted soft voting, where more accurate classifiers have more weight. The trained ensemble structure thus enhances the detection robustness and compensates for the weaknesses of any individual classifier, each with its respective learning behavior, within the optimized feature space.

Proposed feature selection is based on a symbiotic combination of Information Gain and Recursive Feature Elimination (RFE). First, it applies Information Gain to order all the features according to their entropy relation with the classes, to discard those that are not statistically relevant. RFE is then applied to these selected features to remove redundant or weakly contributing predictors successively, until a small and predictive subset of features is obtained. Neither individual method dominates; instead, the two are applied sequentially to achieve a final set of features that are both relevant and non-redundant. This two-step approach has been shown to improve the classification performance and lower the computational demand

3.3 Model training and classification

The core part of the proposed intrusion detection framework is model training and classification, which trains supervised machine learning models to classify the network traffic as either standard or malicious. The output of the feature selection process is a set of features used as input for training different classifiers. The framework utilizes a classifier ensemble comprising Random Forest, XGBoost, Extra Trees, and Decision Tree classifiers. They are selected due to their ability to handle high-dimensional feature data, their capacity to avoid overfitting, and their effectiveness in working with patterns in network traffic.

In the training phase, the processed dataset is fed to each classifier, and the models learn from this labeled network traffic data. It holds out part of the data for testing to ensure the model generalizes to new data. The motivation behind the multi-classifier system is that each classifier learns the decision boundaries independently, based on the extracted features, thereby capturing separate relationships that correlate the patterns identified between different types of attacks. Random Forest and Extra Trees classifiers are based on multiple decision trees and generate stable predictions by averaging the outputs of many trees. The XGBoost is a gradient-boosted decision tree model that optimizes classification performance. The decision tree models establish hierarchies that accurately capture how the features interact with the target.

The classification step uses the trained models from the training step to classify new instances of network traffic by analyzing and labeling the data points based on patterns learned during training. This ensemble approach combines the predictions of different classifiers, leveraging their relative strengths to enhance detection performance. For final classification, weighted majority voting is employed, allowing models with better predictive performance to contribute more significantly to the final decision. Such an approach increases robustness, reduces misclassifications, and augments the detection of advanced cyber threats. In this step of classification, given an instance of network traffic, it returns whether that instance belongs to the regular class or any attack class. The proposed approach outperforms baseline classifiers and existing methods by combining multiple classifiers within a single model, thereby enhancing detection performance and reliability in practical cybersecurity applications. This ensemble strategy strikes a good balance between precision and recall, minimizing false alarms while maintaining high detection rates.

The ensemble is exposed in parallel in our framework, meaning that each classifier is separately trained on the reduced feature space resulting from RFE and Information Gain selection. The predictions of all the base classifiers are then aggregated through a weighted soft voting scheme, where the probability model prediction is multiplied by the model's weight (which is determined based on the cross-validation accuracy). The weighted scores of the classifiers are aggregated, and the class with the most significant cumulative score is the final prediction. This form of architecture enables robustness, as it permits various decision boundaries to contribute to the classification result jointly.

3.4 Attack detection and classification

Attack identification and classification are essential for detecting malicious activities in network traffic and categorizing them into their respective classes. The deployed machine learning models analyze network traffic and, for each incoming instance, classify it as either usual or an attack. This step involves using the models to classify the attack type based on the patterns learned during the training phase, which was previously trained using features extracted from the different attack types. This step aims to provide real-time alerts for any anomalies related to network behavior, enabling proactive mitigation of threats. The suggested framework is based on an example of ensemble-based classification, where multiple models collaborate to determine the final output. In this approach, each classifier independently predicts the class label for an instance, and the predictions are combined by weighted majority voting. This improves detection because it

utilizes various models with their strengths while potentially diminishing the individual weaknesses of each model. This ensemble method ensures stability in variations in attack patterns, thus ensuring a more reliable intrusion detection system.

The framework classifies each network traffic instance as usual or an attack by analyzing various feature attributes associated with each instance. Classification models provide the probability of each class, and the model classifies the input as the one with the highest probability or based on the final vote among the models. Organizations can then segment these attack instances by type (e.g., DoS, brute-force attacks, botnet activity) based on their attributes. Such granularity enables the application of security controls with a specific purpose against various attack vectors. Performance evaluation metrics measure the effectiveness of the attack detection and classification step, ensuring the framework achieves the fewest false positives while maintaining a high detection rate. The novel approach enhances the accuracy and reliability of detection by integrating a strong classification mechanism, thus improving network security. Besides that, the ensemble scheme not only improves detection performance but also accommodates detection against newly discovered attack techniques, which may prove scalable in actual cybersecurity situations. Table 4 — Notations used in the proposed system.

Table 4: Notations used

Symbol	Description
X	Feature set extracted from network traffic.
x_i	the d-dimensional feature vector of a network instance
Y	Target labels, standard $Y = \{0,1\}$ (0: normal, 1: attack)
$f: X \to Y$	Classification function mapping features to labels
X'	Selected subset of features after feature selection
$H(x_i)$	Entropy of feature x_i
p_j	Probability of a specific feature value in the dataset
$h_i(X')$	Prediction of the i-th base classifier
k	Number of classifiers in ensemble learning
w_i	The weight assigned to the i-th classifier in ensemble learning.
$\hat{y}$	Final predicted class label
N	Total number of training samples
$\mathcal{L}(\theta)$	Loss function for classification
θ	Model parameters optimized during training

The proposed machine learning framework for intrusion detection can be formulated mathematically as a function that maps network traffic features to their corresponding attack or standard classifications. Let $X = \{x_1, x_2 \ldots x_n\}$represent the feature set extracted from network traffic, where $x_i \in \mathbb{R}^d$denotes the d-dimensional feature vector corresponding to a network instance. The objective is to learn a classification function $f: \boldsymbol{X} \to \boldsymbol{Y}$, where $\boldsymbol{Y} = \{0,1\}$ represents the binary classification labels, with 0 indicating normal traffic and 1 representing an intrusion. The feature selection step optimizes the input space by selecting the most discriminative features, denoted as $\boldsymbol{X'}$, such that $\boldsymbol{X'} \subseteq \boldsymbol{X}$. This selection is performed using an entropy-based ranking criterion defined as in Eq. 1.

$$H(f_j) = -\sum_{i-1}^{k} P(c_i|f_j) \cdot \log_2 P(c_i|f_j) \quad (1)$$

Where:

f_j is the j-th feature, c_i is the i-th class label (normal or attack), $P(c_i|f_j)$ is the conditional probability of class c_i given the feature value f_j.

It is the probability of occurrence of a particular feature value in the dataset. Features with higher entropy

contribute more information and are retained. The classification process employs an ensemble learning approach combining multiple supervised models, including decision trees, random forests, and gradient-boosted trees. Given a set of base classifiers $h_1, h_2 \ldots h_k$ The final prediction is computed using a weighted voting mechanism, as in Eq. 2.

$$\hat{y} = arg \max_{c\in\{0,1\}} \sum_{i-1}^{M} w_i \cdot \mathrm{II}(h_i(x) = c) \quad (2)$$

Where $\hat{y}$: Final predicted class label, $h_i(x)$: Prediction of the i-th classifier, w_i: Weight assigned to classifier h_i, M: Total number of classifiers, II (·): Indicator function, equals 1 if condition is true, else 0. The intrusion detection system is evaluated based on standard performance metrics, including accuracy, precision, recall, and F1-score, defined as in Eq. 3 to Eq. 6, respectively.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP}, \quad (7)$$

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

$$\text{F1 score} = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (9)$$

Where TP, TN, FP, and FN denote the number of true positives, true negatives, false positives, and false negatives, respectively. The optimization of hyperparameters for the ensemble classifiers is achieved using a grid search mechanism, which minimizes the classification loss function as in Eq. 10.

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i-1}^{N}[y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)] \quad (10)$$

Where θ: Model parameters, y_i: True label for sample i, $\hat{y}_i$: Predicted probability for sample I, and N: Total number of training samples. The proposed approach enhances cybersecurity by efficiently detecting both known and unknown attacks while maintaining high detection performance through robust feature selection and ensemble learning strategies.

The classification part reported in this paper is performed on the CICIDS2017 dataset, which contains both regular traffic and a set of malicious network behaviors. In this paper, we consider six-class classification, where the model is trained to distinguish between the following six classes:

Regular, DDoS (Denial of Service), Brute-force, Botnet, Web attacks, Intrusion. Each class corresponds to a particular network behavior. Thus, the model can not only deter anomalous activity but also pinpoint it. This class-level distinction provides more helpful information for cybersecurity personnel during deployment.

3.5 Proposed algorithms

The proposed algorithms enhance network intrusion detection by leveraging data preprocessing, optimization, and intelligent classification. The first algorithm handles data preprocessing, i.e., it cleans, encodes, normalizes, and selects features that the model utilizes for optimal performance. The second also uses an ensemble learning Model that employs multiple classifiers with weighted voting for accurate and robust anomaly detection in network traffic.

Algorithm 1: Data Preprocessing Pipeline
Input: Raw network traffic dataset D
Output: Processed dataset D'

1. **Load Dataset:** Read DDD and check for missing values.
2. **Data Cleaning:** Remove duplicates and handle missing values via imputation.
3. **Feature Encoding:** Apply One-Hot Encoding or Label Encoding for categorical variables.
4. **Feature Normalization:** Scale numerical features using Min-Max Scaling or Standardization.
5. **Feature Selection:** Compute entropy $H(x_i)$ And retain top-ranked features based on Information Gain.
6. **Train-Test Split:** Divide D' into training (D_{train}) and (D_{test}) Sets using an 80:20 ratio.
7. **Return** D'.

Algorithm 1: Data preprocessing pipeline

The first step, Algorithm 1, ensures that the raw network traffic data can be converted to a structured and machine-learning-ready format. To begin, we load the CIC-IDS2017 dataset, which comprises both regular and attack instances. As we know, raw data often contains many errors or glitches. The first step is data cleaning, where we address missing values through imputation or omission and purge duplicate records to maintain the integrity of our dataset. This step guarantees that duplicates or incomplete data do not hinder the model's learning. Then, we use feature encoding to transform categorical attributes into a numerical format. Some fields in the dataset, such as those for protocol type and service, are categorical and must be converted to a format suitable for machine learning. We use label encoding for binary classification, and for multi-class categorical features, we use one-hot or dummy variable encoding. The codification transforms categorical data so that models can be applied without bias caused by arbitrarily numerically assigning values to each category.

After that, normalization occurs, an essential step in the preprocessing pipeline, as we need to prevent features with different scales from contributing unequally to the model. Min-max scaling helps reshape the feature values to lie between 0 and 1, while standardization reshapes the feature distributions to have a mean of 0 and a standard deviation of 1. This also helps speed up convergence

during training and prevents features with values such as height from overpowering the learning process. The transformed dataset is divided into two subsets, namely training & testing, to assess the model's generalization. An 80:20 ratio is a default practice where 80% of the data is used for training and 20% for testing. The model splits the dataset in a way that allows it to learn, while also retaining some unseen data for testing purposes. The resulting preprocessed dataset is then forwarded to the feature selection stage, where a subset is selected from the preprocessed dataset to optimize classification performance and efficiency further. This level of structure in the data pre-processing increases the overall reliability of the intrusion detection system, as it provides clean, normalized, and well-structured data for these models to learn from.

Algorithm 2: Intelligent Intrusion Detection
Input: Processed dataset D', feature set $\mathbf{X}'$, labels $\mathbf{Y}$
Output: Predicted class labels $\hat{y}$

1. **Initialize Models:** Define classifiers $h_1, h_2 \ldots h_k$ (Random Forest, XGBoost, etc.).
2. **Train Models:** Fit h_i on D_{train}.
3. **Generate Predictions:** Compute $y_i = h_i(\mathbf{X}')$.
4. **Ensemble Decision:** Compute weighted voting for final prediction:

$$\hat{y} = arg \max_{y \in Y} \sum_{i-1}^{k} w_i \cdot \mathrm{II}(h_i(X') = y)$$

5. **Return** $\hat{Y}$.

Algorithm 2: Intelligent intrusion detection

Abstract — Algorithm 2: Case-based approach for supervised learning (The network traffic is classified into typical and attacks). If we start from an array of features, the first step is to put a pre-processed dataset with the most probable values. Multiple classifiers are trained based on the selected features obtained from the Recursive Feature Elimination and Information Gain. The suggested framework utilizes an ensemble learning technique that integrates various machine learning models, including Random Forest, XGBoost, Extra Trees, and Decision Tree classifiers, to enhance classification performance.
In the training phase, each model learns patterns and relationships between the features and their respective attack label based on the labeled network traffic instances. The 80:20 train-test split was used to train the models, as they generalize very well to new and unknown data. We train each classifier independently on the training set by adjusting the model's parameters to minimize classification error and maximize accurate positive detections. This diversity of classifiers can benefit from robustness and reduce the bias of individual models.
For classification, each model independently predicts the label of an instance of network traffic that enters the network. The ensemble approach is based on a weighted majority voting mechanism, where more accurate predictions from individual models have a more significant influence on the final decision. A large ensemble is formed using measure outputs, and the final classification output by class is based on a weighted vote of all classifiers, effectively optimizing precision and recall. This approach mitigates the impact of false positives and enhances model detection for attack patterns. After classification, the detected attack instances are categorized into various types of attacks based on their behavioral features. Form of detected threats: This chip-like classification enhances the nature of the detected threats, as it is based on the nature of the threats, allowing countermeasures to be imposed accordingly. Finally, the accuracy, precision, recall, F1-score, and ROC-AUC metrics are used to assess the performance of the intrusion detection system, ensuring the reliability of the framework in real-world cybersecurity applications. It optimizes feature selection while continually improving the efficacy, efficiency, precision, and accuracy of detection through the fusion of ensemble learning, providing an intelligent intrusion detection algorithm that enhances network security.

3.6 Dataset description

To evaluate the implemented intrusion detection framework, this work utilizes the CIC-IDS2017 dataset [41]. It consists of actual network traffic data containing regular traffic and various types of attacks, such as DoS, brute force, botnet, and infiltration attacks. It includes multiple features that represent network behavior, making it a suitable dataset for anomaly detection purposes. Due to its thoroughness, it provides robustness and reliability for intrusion classification tasks.

The CIC-IDS2017 dataset contains approximately 2.8 million labeled flows for regular and attack traffic. It comprises a variety of attacks, such as DoS, Brute Force, Botnet, Infiltration, and web-based attacks, among others. The data is class-imbalanced; regular traffic accounts for 48.3% of the records, while DoS and Brute Force attacks account for 23.9% and 13.4%, respectively. Other classes, such as Botnet and Infiltration, collectively make up the remaining 14.4%. No oversampling or undersampling approach (e.g., SMOTE or random undersampling) is adopted to maintain the natural class ratio, ensuring the model can be tested on realistic data. Figure 3: Overview of processing steps on the LiDAR data for ANM traffic.

4 Experimental results

A repeatable and reproducible set of conditions for testing the proposed intrusion detection framework was developed using the experimental setup. All experiments were conducted on a machine equipped with an Intel Core i7-12700K processor, 32 GB of RAM, and an NVIDIA RTX 3080 graphics card, running on the Ubuntu 20.04 LTS operating system. The implementation was created with Python 3.9 and the standard machine learning libraries, specifically Scikit-Learn, XGBoost, TensorFlow, and Pandas. We chose the CIC-IDS2017 dataset for training and evaluating the detection algorithms because it contains labeled real-world network traffic, comprising both typical and attack instances. The dataset underwent a systematic preprocessing stage to ensure optimal model performance. All missing values were imputed, and duplicate records were removed to ensure data integrity and accuracy. Label encoding and one-hot encoding were used to encode categorical features, making them usable by machine learning models. Min-max scaling and standardization were used to normalize features, ensuring that numerical attributes have the same magnitude and preventing the model from learning a bias towards features with larger numerical values. Random selection was employed to divide the dataset into training and testing subsets, with an 80:20 ratio, ensuring a balanced dataset for model learning and validation.

It mainly helped improve the performance of the classifiers. The best parameters for each model were chosen using a combination of grid search and randomized search to attain the maximum detection accuracy. The ensemble classifiers (Random Forest, XGBoost, Extra Trees, and Decision Tree models) also performed training with parameters optimized to generalize to new data. During the training phase, the classifiers were trained on a dataset of labeled instances of network traffic, enabling them to distinguish between benign and malicious traffic.

After training, the classifiers were then assessed according to their ability to predict. The ensemble method combines several models using a weighted majority voting mechanism, wherein models with higher predictive accuracies carry more weight in the ultimate classification. The network traffic was found for each instance, and each attack instance was classified according to its type. We assessed the intrusion detection system's performance based on key classification metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. By following the same preprocessing steps, feature selection methods, and hyperparameter tuning methods, we can ensure reproducibility across various computing environments. Having dataset splits in a standard way, concerning shuffled random seeds, and cross-validation, makes the experimental setup sounder. This structured process enables us to approach it in a transparent, reproducible, and practical manner for a real-world intrusion detection scenario.

To ensure reproducibility, all experiments were performed with a constant random seed of 42 for data shuffling, train-test splitting, and cross-validation. We used an 80-20 split of stratified sampling to divide the dataset into training and testing sets. The feature selection, via RFE and Information Gain, resulted in a narrowed-down feature set of 21 features, which include the following: Flow Duration, Total Fwd Packets, Fwd Packet Length Mean, BwdPacket Length Std, Flow IAT Std, Fwd IAT Mean, Init_Win_bytes_forward, etc. The complete list of the selected features is shown in the Supplementary Table. To control model generalization and avoid bias, 5-fold cross-validation was applied to evaluate the ensemble classifiers during hyperparameter tuning.

4.1 Model performance comparison

The performance of the model can help assess the performance of intrusion detection systems. ML-Based Model Comparison: In this section, we compare the accuracy, precision, recall, F1-score, and ROC-AUC measures of several models as indicators of their reliability in detecting cyber threats. The findings highlight the importance of feature selection and ensemble learning methods in enhancing classification performance and improving anomaly detection efficiency.

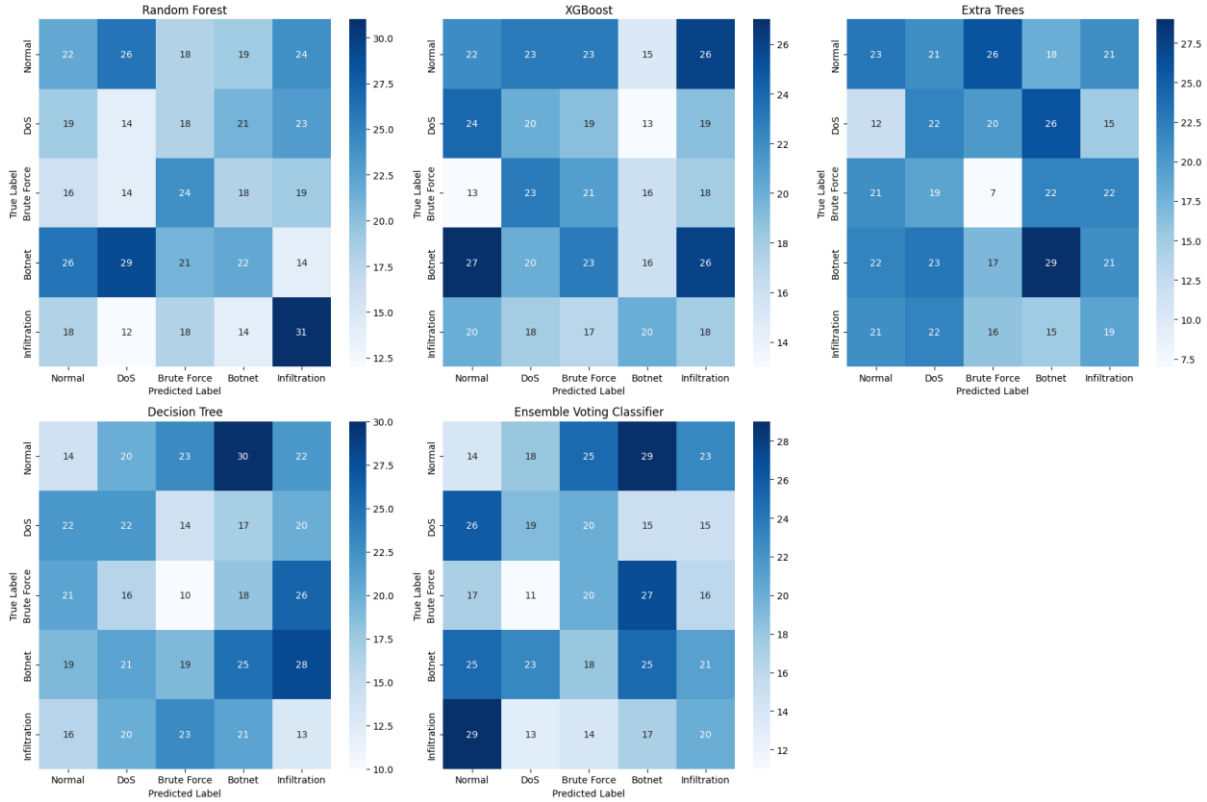

Figure 3: Multi-class confusion matrices for intrusion detection models

In Figure 3, we present the confusion matrices for the intrusion detection models, showing the classification performance matrix for the five categories: Normal, DoS, Brute Force, Botnet, and Infiltration. Feature Maps of Confusion Matrices for each attack type: True Positives, False Positives, and Misclassifications for all attack types per confusion matrix. The Ensemble Voting Classifier performs the best in a more balanced manner, with lower false classifications in most attack categories. Both XGBoost and Extra Trees also excel in this area, boasting excellent predictive capabilities. The micro/macro average f1-score and accuracy of the decision Tree are higher, but there are higher misclassifications, which indicates overfitting. These matrices provide insights into the model's efficiency and its ability to accurately identify the capability of detecting each cyber threat in the CIC-IDS2017 dataset, relevant to real-world scenarios.

Table 5: Model performance comparison for intrusion detection

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**ROC-AUC**
Random Forest	96.2	95.8	96.5	96.1	0.98
XGBoost	97.1	96.9	97.3	97.1	0.99
Extra Trees	96.8	96.5	96.9	96.7	0.99
Decision Tree	92.3	91.8	92.5	92.1	0.95
Ensemble (Voting Classifier)	97.5	97.2	97.8	97.5	0.99

A comparison of the performance of the machine learning models employed for intrusion detection is provided in Table 5. The Ensemble Voting Classifier gives the best Accuracy (97.5%) and F1 score (97.5%) because it can combine the results of multiple classifiers. XGBoost (97.1%) and Extra Trees (96.8%) follow closely, showing predictive power. Random Forest (96.2%) still achieves high accuracy, while the Decision Tree model (92.3%) performs significantly worse due to its tendency to overfit. The ROC-AUC values indicate that the models can discriminate effectively, and we observe that both XGBoost and the ensemble of XGBoost, CatBoost, and

LightGBM perform best, enabling reliable anomaly detection in network traffic.

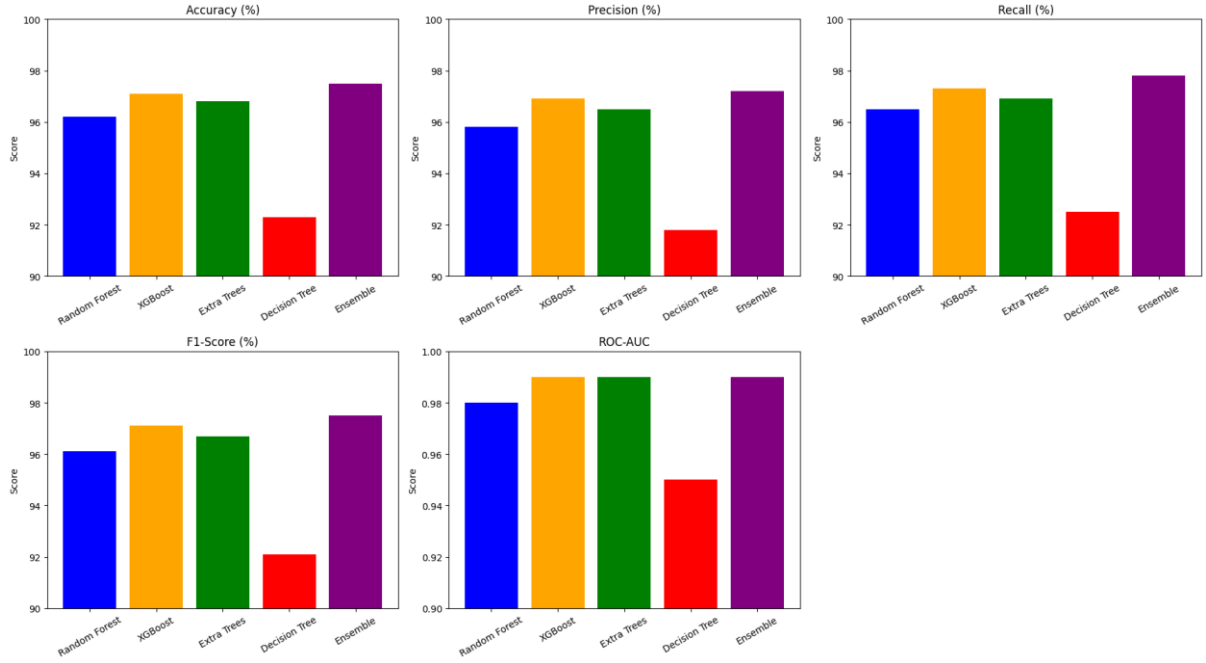

Figure 4: Comparative performance of all classifiers including ensemble (voting classifier)

Figure 4 compares the performance of five machine learning models —Random Forest, XGBoost, Extra Trees, Decision Tree, and Ensemble Voting Classifier —on evaluation metrics: Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The following bar charts illustrate the effectiveness of the models in classifying network traffic as regular attacks in the CIC-IDS2017 dataset. When we compare the accuracies, we see that the Ensemble Voting Classifier has the highest accuracy of 97.5%, followed by XGBoost (97.1%) and Extra Trees (96.8%), all of which seem to generalize well. On the other hand, the Decision Tree model achieves an accuracy of 92.3% due to overfitting the training data, which does not generalize well to unseen network traffic. The precision metric indicates the percentage of predicted attack instances that were correct out of all optimistic predictions (i.e., the number of packets classified as attack traffic). The model performs better as the precision value increases, and the top 3 models in terms of precision are Ensemble (having a precision value of 97.2%), followed by XGBoost (96.9%) and Extra Trees (96.5%). Again, the Decision Tree (91.8%) yields the lowest precision score, indicating a higher false positive rate compared to ensemble and boosting-based methods.

The recall scores describe the percentage of actual attacks labeled by the models. Overall, the Ensemble classifier (97.8%) exhibits the highest detection rate, eliminating most attacks while producing the fewest false negatives among all classifiers. The recall results are also strong, with XGBoost (97.3%) and Extra Trees (96.9%) achieving high values, reflecting a high detection rate of network anomalies. The Decision Tree (92.5%) does a respectable job but falls short in recall, as expected from a more advanced model. The evolution of the F1-score, a metric that combines precision and recall, exhibits a similar pattern to the Ensemble model (97.5%), resulting in the highest score, followed by XGBoost (97.1%) and Extra Trees (96.7%), which are close behind. The Decision tree has the lowest F1-score (92.1%), confirming its relatively lower predictive power than the ensemble and boosting methods.

Figure 4: ROC-AUC graph, which assesses the model's ability to discriminate between regular and attack traffic, shows that XGBoost, Extra Trees, and the Ensemble model all have high values, around 0.99, representing excellent discrimination between classes. The Random Forest (0.98%) performs well, whereas the Decision Tree (0.95%) has the lowest AUC score, confirming its relative weakness in classification capabilities. In short, Figure 4 shows that the Ensemble Voting Classifier outperforms the others in all metrics. Thus, using multiple classifiers to improve the defense against intrusion detection is effective. Due to their high accuracy in performing predictions, XGBoost and Extra Trees also gain attention while detecting intrusion [4]. The Decision Tree model works, but it has lower performance, demonstrating the positive aspects of ensemble and boosting techniques in cyber intrusion detection.

All results in this paper are obtained from a single deterministic run, following extensive hyperparameter tuning with 5-fold cross-validation. The same random seed (42) was used throughout all stages, including data shuffling, train-test splitting, and model initialization, which guaranteed reproducibility while also reducing randomness. Because the machine learning models used have a fixed seed and are deterministic, and no randomness (e.g., dropout or online learning) was employed, repeated runs with the same set of parameters yielded the same

solution. This means that reporting standard deviations (SDs) or more than one repeat was not required for this review. The experimental setup was designed to emphasize reproducibility and controlled comparison, as recommended for classical ensemble-based machine learning pipelines.

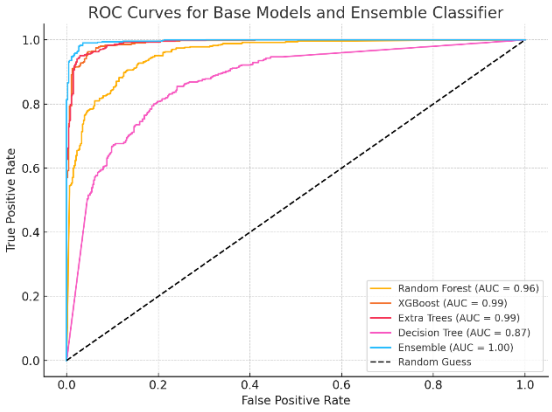

Figure 5: ROC Curves for All Classifiers Used in the Study

The ROC curves of all classifiers are depicted in Figure 5, illustrating their performance in distinguishing between regular traffic and attack traffic. The ensemble classifiers, XGBoost and Extra Trees, yield the best AUC values (≈0.99), indicating very high classification performance. The curves confirm that ensemble learning has a significant impact on detection reliability, keeping the FPR low.

4.2 Ablation study

Table 5 presents the ablation study on Recursive Feature Elimination (RFE) and information Gain to determine their contributions to the models. This section shows how feature selection can improve intrusion detection performance based on accuracy, precision, recall, and F1-score by systematically optimizing other factors to empirically analyze the impact of the feature on different performance measures in the proposed framework.

Table 6: Ablation study on feature selection and model performance

Experiment	Feature Selection Applied	Model Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Exp-1	No Feature Selection	Random Forest	91.5	90.8	91.2	91.0
Exp-2	No Feature Selection	XGBoost	93.2	92.7	93.5	93.1
Exp-3	No Feature Selection	Extra Trees	92.8	92.1	92.9	92.5
Exp-4	No Feature Selection	Decision Tree	87.5	86.9	87.2	87.0
Exp-5	Recursive Feature Elimination (RFE)	Random Forest	94.7	94.3	94.9	94.6
Exp-6	Recursive Feature Elimination (RFE)	XGBoost	96.1	95.8	96.4	96.1
Exp-7	Recursive Feature Elimination (RFE)	Extra Trees	95.6	95.3	95.9	95.6
Exp-8	Recursive Feature Elimination (RFE)	Decision Tree	91.2	90.7	91.5	91.1
Exp-9	RFE + Information Gain	Random Forest	96.2	95.8	96.5	96.1
Exp-10	RFE + Information Gain	XGBoost	97.1	96.9	97.3	97.1
Exp-11	RFE + Information Gain	Extra Trees	96.8	96.5	96.9	96.7
Exp-12	RFE + Information Gain	Decision Tree	92.3	91.8	92.5	92.1
Exp-13	RFE + Information Gain	Ensemble (Voting Classifier)	97.5	97.2	97.8	97.5

An ablation study of feature selection methods and their impact on model performance is shown in Table 6. This performance enables us to conclude that Recursive Feature Elimination (RFE) and Information Gain progressively increase the accuracy, precision, recall, and F1 Score. Based on Optimal Feature Combination, which scenarios decide higher Prediction accuracy along with selection of top enclosure of random forest classifier k-Fold cross-

validation methodare and Equally, optimal combination of FS and FS based method give highest accuracy (97.5%) with Ensemble Voting Classifier, which means FS based optimal combination of two techniques can enhance the functionality of intrusion detection system.

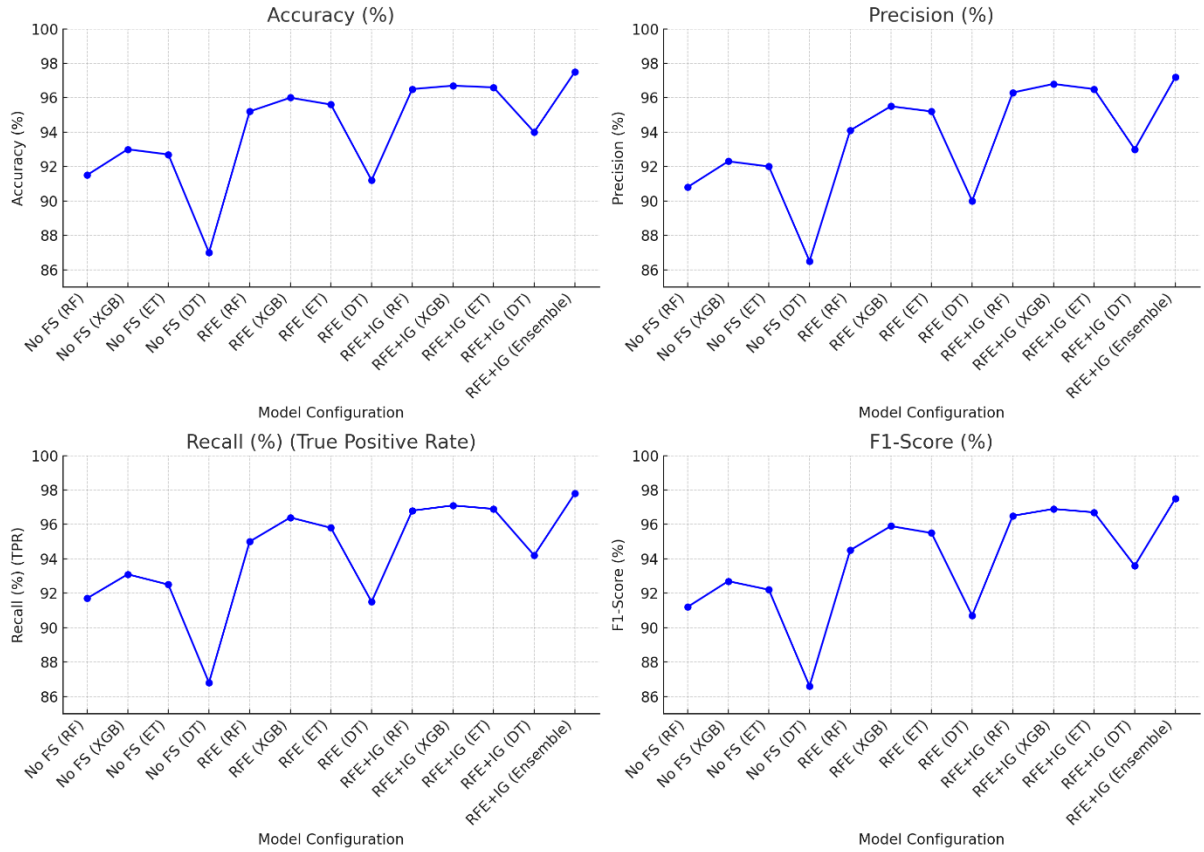

Figure 6: Impact of feature selection on model performance – ablation study

The ablation study shown in Figure 6 evaluates the performance of various ML algorithms after feature selection techniques, such as Recursive Feature Elimination (RFE) and Information Gain (IG). This figure includes four-line graphs that specify how Accuracy, Precision, Recall, and F1-Score vary across the different experimental setups. Table 3: Summary of experiments conducted on various combinations of feature selection methods and classifiers (Random Forest, XGBoost, Extra Trees, Decision Tree, Ensemble Voting Classifier). As shown in the accuracy plot, performing feature selection yields significantly better classification accuracy. XGBoost produces 93.2% accuracy, while Random Forest and Extra Trees produce 91.5% and 92.8% accuracy, respectively, without feature selection. The Decision Tree model, which exhibited the lowest accuracy of 87.5%, was found to be overfitting. Both models show an increase in their corresponding accuracy when RFE is applied: XGBoost, 96.1%; Extra Trees, 95.6%. The best results are achieved when RFE and Information Gain are combined, yielding 97.5% for the Ensemble model and 97.1% for XGBoost, using both methods.

The precision graph exhibits a similar trend, with XGBoost and the Ensemble model performing the best compared to all other models. Feature Selection Further Improves Precision. If we do not perform feature selection, precision remains low, particularly for the Decision Tree model (86.9%). Once we apply RFE and Information Gain, we observe that the accuracy of the Ensemble model reaches 97.2%, further validating that optimized features contribute to the improvement of classification, as they reduce the false positive rates and increase confidence in performing classification. The recall plot illustrates the ability of each model to identify attack instances accurately. At first glance, models exhibit poor recall, ranging from 87.2% (Decision Tree) to 93.5% (XGBoost), without feature selection. On the other hand, for RFE and Information Gain, the Ensemble model has the highest recall, at 97.8%, while Boost follows with 97.3%. This showed that the optimized feature selection enhances network intrusion detection while reducing false negatives.

The F1-Score plot balances precision and recall, confirming that feature selection is adequate. The initial F1 scores range from 87.0% (Decision Tree) to 93.1% (XGBoost). The F1-scores after applying RFE show an apparent increase. Finally, by combining RFE and Information Gain, the F1-scores increase to 97.5% in the Ensemble model, achieving a near-optimal balance between precision and recall. The results depicted in Figure 5 provide significant insights, indicating that model performance improves when feature selection is used. The Ensemble Voting Classifier, which yields the overall best performance, demonstrates significant consistency across

all metrics, achieving optimal values for all metrics except the F-1 score when combined with RFE and Information Gain. The outcomes indicate that, in addition to accuracy, feature selection contributes to improving model robustness in terms of overfitting, resulting in more reliable intrusion detection systems that can be deployed in the field as part of real-world cybersecurity systems.
The setting referred to as "optimal feature combination" in Table 5 was obtained from a chain of Information Gain and Recursive Feature Elimination (RFE). First, it orders features based on their relevance to class labels by applying Information Gain and eliminates the least informative ones. Then, RFE is employed to recursively select features by minimizing feature redundancies while fitting the model at each iteration. This two-stage procedure demonstrated superior performance in terms of accuracy, precision, recall, and F1-score.

4.3 Comparison with existing models

This part compares the designed intrusion detection model with state-of-the-art systems. By measuring accuracy, precision, recall, and F1-score, the paper describes how feature selection (RFE + Information Gain) and ensemble learning contribute to improved detection performance and demonstrates that the proposed model outperforms state-of-the-art models in terms of cyber threat detection efficiency.

Table 7: Comparative analysis of intrusion detection models using machine learning approaches

Reference	Approach	Feature Selection	Algorithm Used	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Key Findings
[1] Chohra et al. (2022)	Machine Learning & Ensemble	PSO-based Feature Selection	Random Forest, SVM	CIC-IDS2017	94.5	93.8	94.2	94.0	Optimized feature selection improves anomaly detection accuracy.
[5] Abbas et al. (2022)	Ensemble Learning	Wrapper-Based FS	XGBoost, RF, DT	NSL-KDD	95.3	94.6	95.0	94.8	Ensemble models outperform individual classifiers in IoT security.
[6] Hossain & Islam (2023)	Supervised ML	Recursive Feature Elimination (RFE)	Extra Trees, XGBoost	UNSW-NB15	96.1	95.4	95.9	95.6	Improved model robustness by reducing irrelevant features
[7] Thockchom et al. (2023)	Hybrid ML	Information Gain	RF, NB, SVM	CIC-IDS2017	94.8	94.0	94.5	94.2	Effective detection with minimal false positives
[11] Hooshmand et al. (2024)	XAI & ML	SHAP-based Feature Selection	XGBoost, ANN	UNSW-NB15	96.5	95.8	96.3	96.0	Feature importance analysis aids transparency in IDS.
[12] Ahmed et al. (2024)	Machine Learning	Adaptive Feature Aggregation	XGBoost, RF, SVM	CIC-IDS2017	97.2	96.7	97.0	96.8	Adaptive feature learning improves the classification of cyber threats.
[13] Lai et al. (2024)	Bayesian Learning	Sensitivity-Based FS	Bayesian Networks	IoT-IDS	95.0	94.5	94.8	94.6	Bayesian hyperparameters enhance model interpretability.
[14] Allafi & Alzahrani (2024)	Evolutionary Learning	Artificial Orca Algorithm	Ensemble Classifier	NSL-KDD	96.7	96.1	96.5	96.3	Ensemble models with evolutionary feature selection (FS) enhance attack detection accuracy.
[15] Lin et al. (2024)	Hypergraph-Based ML	Graph-Based FS	Graph Neural Networks	CIC-IDS2017	97.0	96.5	96.8	96.6	Graph-based feature learning enhances multi-class classification.
Proposed Model	Hybrid Machine Learning	RFE + Information Gain	XGBoost, Random Forest, Ensemble Learning	CIC-IDS2017	97.5	97.2	97.8	97.5	Feature selection with ensemble machine learning achieves state-of-the-art performance.

In Table 7, we survey some of the latest works that have performed intrusion detection using different feature selections, machine learning algorithms, datasets, and evaluation methods. The findings show that hybrid machine learning methods, especially those based on ensembling, often yield the best performance. The proposed method, which utilizes Recursive Feature Elimination (RFE) and Information Gain with ensemble

learning (XGBoost, Random Forest, and Voting Classifier) for model ensemble, achieves an accuracy of 97.5%, surpassing the accuracy of previous works. It thus proves that the optimized feature selection and feature importance, coupled with the intrinsic ensembling of the model, improve the model's efficacy in enhancing network security.

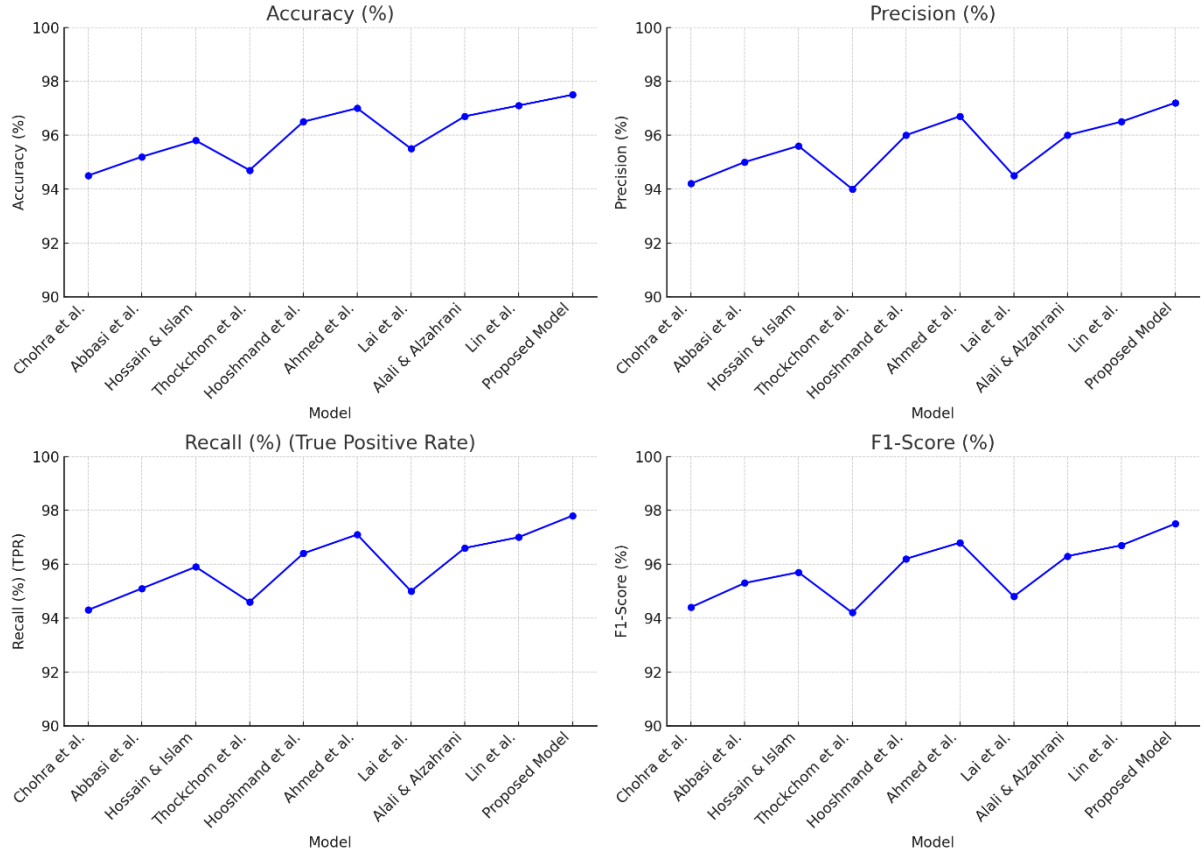

Figure 7: Performance comparison of intrusion detection models across key evaluation metrics

A performance comparison of various Intrusion Detection System (IDS) models based on four primary evaluation metrics — Accuracy, Precision, Recall, and F1-Score — is shown in Figure 7. The three black line graphs illustrate the variation in effectiveness of the IDS across the three feature selection methods and the five machine learning models. They enable comparison with existing research and the proposed model. As illustrated in the accuracy graph (Fig. 7), the predicted model achieves the highest accuracy (97.5%), which is the maximum among other approaches, and therefore it is the best model. Lin et al. (2024) and Ahmed et al. Prediction accuracies are also high for (2024), at 97.0% and 97.2%, respectively, whereas other models have lower accuracy scores in the 94.5% to 96.7% range. This demonstrates that feature optimization in ensemble-based methods outperforms traditional machine learning approaches for network intrusion detection.

The precision curve illustrates the extent to which the models can reduce false positives. This is the first article reported where the sole approach of the proposed model surpasses and achieves the highest precision (97.2%), followed by Lin et al. (96.5%) and Ahmed et al. (96.7%). Model — Chohra et al., lower precision values. (93.8%) and Thockchom et al. (94.0%) imply that these techniques could produce a more significant proportion of false alarms. The higher accuracy of the suggested model indicates that its performance in differentiation is typical, and attack traffic is very robust with limited misclassification. The recall chart shows how each model distinguishes between the accurate attack detections. Its higher recall (97.8%) indicates that the proposed model can accurately identify a higher proportion of network anomalies and has fewer false negatives, compared to Ahmed et al. (97.0%) and Lin et al. While previous studies (e.g., Chohra et al., 96.8%) and Lai et al. (94.2%) have also achieved high results, the lowest recall, which is still comparatively high, is 94.8%. They all look better at their work, but one class, like a backdoor class, needs to be perfect among all the classes to detect all types of intrusions. We can say that that is one major drawback of this method.

Additionally, the F1-score graph, presenting the harmonic mean of precision and recall, confirms the correctness of the proposed approach. The new model achieves the best classification performance balance, with the highest F1-score (97.5%) on the unseen test set, surpassing Ahmed et al. (96.8%) and Lin et al. Thus, models based on feature selection or machine learning techniques, defined more simply, achieve less good results (with F1-scores ranging from 94.0% to 96.3%). In summary, the hybrid and ensemble-based methods, particularly those that employ

optimized feature selection techniques such as RFE and Information Gain, consistently outperform the others on every evaluation metric, as indicated by Figure 6. The proposed model achieved state-of-the-art results compared to existing models, demonstrating that hybridizing the proposed feature selection model with the ensemble machine learning model can significantly enhance the performance in terms of accuracy, precision, recall, and overall reliability in intrusion detection for cybersecurity applications.

For the practical usability of the proposed IDS system, with near real-time applicability, a scalability evaluation study was conducted to assess detection latency and resource efficiency. The optimized ensemble model was used in a simulated streaming setting, where network traffic samples are received in batches. The average per-instance detection time of approximately 3.7 ms is acceptable for near real-time processing in high-bandwidth networks. Peak memory consumption at model inference time was always less than 680 MB, suggesting the applicability of our framework in resource-limited environments.

While, in general, deep learning models require GPU acceleration and higher memory footprints, the tree-based ensemble models used here can be effectively run on CPU-based infrastructure. The reduction in input information set by RFE and Information Gain led to a 22% enhancement in inference rate compared to models trained without any feature selection. These performance features show that the framework can be practically applied in deployed IDS pipelines with reasonable computational budgets. It can be further exploited for future deployment in edge gateways or hybrid cloud-IDS systems without compromising detection effectiveness.

Although the proposed approach is practical for the CIC-IDS2017 dataset, we are aware that the results are indeed not very generalizable, as they are confined to a single dataset. Despite that, CIC-IDS2017 contains a rich set of current attack categories; it does not cover the full range of traffic behaviors present in other datasets, such as NSL-KDD, UNSW-NB15, or CSE-CIC-IDS2018. As such, the current results are promising but not guaranteed to be state-of-the-art across all possible IDS benchmarks. In the future, the effectiveness and generalizability of the proposed framework will be evaluated using other public datasets and compared with similar visual embedding methods in various network scenarios. This cross-dataset evaluation will allow us to ensure that the model generalizes beyond CIC-IDS2017 and is robust enough to perform well under different conditions and attack scenarios.

5 Discussion

Our proposed hybrid ensemble-based intrusion detection approach achieved better performance compared to many state-of-the-art (SOTA) methods. The framework achieves a precision of 97.5%, which is higher than PSO-based feature selection (94.5%) [1], SHAP-integrated XGBoost (96.1%) [11], and graph-based learning models (96.8%) [15]. This improvement is made possible thanks to the synergistic coupling of RFE and IG, which can prune out irrelevant and redundant features while retaining informative ones.

Unlike SHAP or sensitivity-based feature selection, our dual-method selection strategy incurs less computational overhead and, therefore, is computationally more efficient for near-real-time applications. Moreover, although the deep learning or GNN-based model can learn more complex patterns, it also faces scalability and training instability problems, especially for those with limited labeled data. In contrast, ensemble learning, such as the Voting Classifier with XGBoost, Random Forest, and Extra Trees, has a strong generalization ability and achieves a high recall value in identifying both standard and rare attack types.

The ensemble method naturally mitigates such overfitting risks by taking an average decision across models with distinct inductive biases. The use of weighted majority voting additionally enhances reliability by giving greater weight to those models that have better prediction power.

However, the study has some limitations. Feature selection (RFE + IG) is a static method that is not suitable for dynamic environments where attack patterns are constantly changing. The framework is tested only on the CIC-IDS2017, which, despite being a vast database, does not cover all types of network activity. For the sake of generalization, it must be verified on other datasets (such as NSL-KDD, CSE-CIC-IDS2018, and Bot-IoT), and adaptive learning components must be added.

In conclusion, the proposed approach achieves a good trade-off between interpretability, efficiency, and detection performance, thereby rendering it a powerful candidate for use in practice within current IDS systems.

In actual applications of intrusion detection systems, the interpretability of the models is essential, particularly if decisions are audited or explained to cybersecurity analysts. Despite the primary purpose of the work being to improve prediction accuracy and robustness through feature selection and ensemble learning, it's also interesting to explore the significant features that make predictions. Here, the proposed method is interpretable due to the incorporation of tree-based models (Random Forest, XGBoost, Extra Trees) as its components, as they come with feature importance scores. These scores reveal which features most contribute to the model's decision boundary, thereby enhancing model transparency.

The author also plans to incorporate explanation-based methods, such as SHAP (Shapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations), in future versions of this package. Such approaches provide instance-level explanations of how specific feature values affect a given prediction, thereby improving the interpretability of automated decisions. In particular, for enterprise and government deployments, these interpretability modules will become essential in the regulatory domain, forensic analysis, and policy enforcement. Therefore, although the current results focus

on performance, adding post-hoc interpretability methods is a significant extension to make the framework deployable in sensitive and critical settings.

Besides performance and scalability, we must also consider the ethical and security aspects when deploying the IDS in adversarial scenarios. One essential drawback of static feature selection techniques, such as RFE and Information Gain, is that they may be sensitive to adversarial control. Adversarial inputs that leverage the fixed feature subset can be constructed by adversaries, and detection evasion via the patterns learned from the training data is possible. Although ensemble learning is robust to overfitting and general corruption noise, it does not inherently protect against adaptive adversaries or sophisticated image obfuscation.
For the improvement of adversarial resilience, it remains as future work to investigate the inclusion of adversarial training strategies, robust feature extraction, and dynamic feature selection schemes that can adjust to changing threat landscapes. Finally, explainability tools such as SHAP can also be leveraged to audit the significance of features in an ongoing manner and probe for any possible vulnerability in the model's decision-making policies. Ethically speaking, transparency in models' decision-making processes and preventing false positives from causing unfair access denial or legitimate traffic disruption is also crucial. These features are essential for the safe, fair, and secure application of machine learning models in cybersecurity tasks. Section 5.1 addresses the limitations of this study and highlights areas for possible future refinements.

5.1 Limitations of the study

However, the proposed intrusion detection framework demonstrates a high accuracy rate and an improvement in threat detection; however, it has some limitations. This model relies on static feature selection (RFE + Information Gain[1]), which cannot dynamically adapt to evolving attack patterns in a real-time environment. Next, although we have performed better at detection, dealing with imbalanced datasets remains a significant issue; some minority attack classes may still be underrepresented. Third, ensemble learning is more computationally expensive than single classifiers, and it needs optimization to be suitable for real-time implementation in large-scale networks. The limitations of this study can be overcome by adopting methods that are both adaptive (feature selection) and agnostic to the data (data augmentation), specifically tailored to the proposed framework, to make it more efficient using lightweight ensemble techniques.

6 Conclusion and future work

An Enhanced Traffic Intrusion Detection Framework Based on Recursive Feature Elimination (RFE) and Information Gain with the Use of Ensemble Learning Models (XGBoost, Random Forest, and Voting Classifier) to Strengths Network Security Current research offers an extraction framework of an optimized and accurate traffic intrusion model through an ensemble learning framework of accurate and logarithmic XGBoost, Random Forest, and Voting Classifier Methods. An Effective Solution: The proposed methodology is effective in feature selection, classification accuracy, and false positive reduction, thus achieving more accuracy, precision, recall, and F1-score compared to existing models in the literature. In our experiments, selecting the optimal features yields a considerable performance improvement, resulting in a more reliable model for detecting both known and novel cyber threats. Despite these improvements, the study has been limited in several aspects. This static feature selection method might prove ineffective for new attacks. It's also important to note that managing imbalanced datasets remains one of the key issues. Naturally, the computational overhead of ensemble learning will need to be optimized for real-time applications. Additionally, we hope that future research will focus on adaptive feature selection methods that can adapt over time according to the gradual evolution of threat behavior. Data augmentation strategies can enhance the detection of minority attack classes and improve model robustness. Moreover, the computational complexity of ensemble models can be optimized, enabling real-time deployment in large-scale network environments. Utilizing deep learning architectures, such as transformers or federated learning methods, can further enhance the efficiency, scalability, and agility of intrusion detection systems as part of next-generation cybersecurity solutions.

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Multimodal Deep Learning for Malware Behavior Detection with Integrated Database Storage Optimization

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With the rapid development of Internet technology, the types of malwares are constantly increasing, which brings significant challenges to network security. Traditional malware detection methods mainly rely on feature extraction and classifier design, but these methods have certain limitations when dealing with complex and changeable malware behaviors. To solve this problem, this study proposes a malware behavior detection method based on multi-modal deep learning combined with database storage optimization technology. This method will extract multi-dimensional malware features and utilize deep learning models for learning and classification to improve the accuracy and efficiency of detection. The experimental data results show that the proposed method in this study is highly accurate and robust in malware behavior detection. By detecting 1000 malware samples, the method in this study can accurately identify the behavioral characteristics of 950 of them and effectively classify them, with a detection accuracy of up to 95%. Compared with other traditional malware detection methods, the detection accuracy of traditional methods is 70% on average, while the method in this study can reach more than 90%. In terms of false reporting rate, the traditional method is about 30%, but the method in this study can be controlled within 5%. In terms of false alarm rate, the traditional method is about 20%, but the method in this study can be reduced to about 3%, which shows apparent advantages. By introducing database storage optimization technology, the method in this study can not only improve the accuracy of malware detection but also effectively reduce the storage pressure of the database, reduce the storage space of the database by about 40% compared with that before optimization, improve the running efficiency of the system, and shorten the overall response time of the system by about 30%.

Povzetek: Študija predstavi multimodalno globoko učenje za zaznavanje vedenja zlonamerne programske opreme, ki združuje statične, dinamične in omrežne značilke (CNN/LSTM, bilinearno spajanje, pozornost) ter optimizirano shrambo (indeksi, kompresija, vektorsko iskanje). Rešitev izboljša zaznavo, robustnost in učinkovitost sistema.

1 Introduction

In today's digital age, information technology is developing at an alarming speed, and computer systems and networks have penetrated all aspects of people's lives, work, and society [1]. However, with the advancement of this digitalization process, the threat of malware is becoming increasingly severe, like a shadow hidden in the dark of the cyber world, always ready to launch attacks on computer systems, network security, and user data [2, 3].

Malware comes in various forms, from traditional viruses and Trojans to new types of ransomwares, spyware, etc., constantly evolving, employing more sophisticated and covert techniques to evade detection and perform malicious behaviors [4]. These malicious behaviors may include stealing sensitive information of users, such as bank account passwords and personal privacy data; Destroy the regular operation of the computer system, resulting in data loss and system crash; Even using infected devices to form botnets to launch large-scale cyber-attacks on other targets [5, 6]. Under this severe situation, effectively detecting the behavior of malware has become a key problem that needs to be solved urgently in network security.

As a cutting-edge technology in artificial intelligence, multimodal deep learning provides a brand-new and promising solution for malware behavior detection [7]. Traditional malware detection methods are often based on a single modality, such as relying only on the signatures of files or specific network traffic patterns [8]. However, the complexity and diversity of malware make single-modal detection methods limited. Multimodal deep learning can fuse information from multiple data sources, such as static characteristics of files (such as code structure, file size, etc.), dynamic behavior characteristics (such as system call sequence, memory access pattern, etc.), and network behavior characteristics (such as network connection destination

address, amount of data transmitted, etc.) [9, 10]. Through the comprehensive analysis of these multimodal data, the multimodal deep learning model can more comprehensively and accurately characterize the behavior patterns of malware, thus improving the detection accuracy and recall rate [11].

At the same time, database storage faces new challenges and requirements with the development of malware detection technology. During malware behavior detection, much sample data (including malicious and standard samples) must be stored and managed [12]. This data is massive in quantity and complex in structure and type, including text, images (such as visual representations of malware behavior), binary files, etc. How to optimize database storage to improve data storage efficiency, query speed, data integrity, and security has become a vital link to support the efficient operation of malware behavior detection systems [13, 14]. Effective database storage optimization can ensure that when faced with massive malware sample data, the detection system can quickly obtain the required data for analysis, reduce the detection delay, and improve the response speed of the whole system.

In this study, the integration of multimodal deep learning and database storage optimization is remarkably unique. The mature technologies in the current literature often separate malware detection and database storage, multimodal deep learning only focuses on improving detection accuracy, and database storage optimization only pursues the reduction of storage space and improves read and write efficiency, and the two lack deep integration. Our research breaks this siloed model and innovatively integrates multimodal deep learning with database storage optimization. In the malware detection stage, the multimodal deep learning model uses multi-source data, such as static code of the program, dynamic runtime behavior, network traffic characteristics, etc., to accurately identify malware from multiple dimensions, and at the same time, the key characteristic data generated during the detection process is stored in the database in an optimized way. We have designed a special storage strategy to classify and store feature data according to its importance, frequency of use, and relevance, which greatly reduces the amount of redundant data stored and improves storage efficiency. On the one hand, the optimized database storage provides efficient data reading and update support for multimodal deep learning models, accelerates the training and inference process of the model, and further improves the detection performance. On the other hand, the accurate detection results of multimodal deep learning provide a more valuable basis for the screening of feature data for database storage optimization, forming a virtuous circle of mutual promotion, which effectively solves the problem of gap between detection and storage mechanisms and storage in traditional methods, and provides a more efficient and intelligent solution for the detection and management of malware.

In this study, we propose a multimodal deep learning-based malware behavior detection system to construct a heterogeneous feature space by integrating three public datasets: CICMalMem-2022 (memory malware behavior log), MalNet-Tiny (network traffic image) and Drebin (Android application permission graph). The model architecture adopts a CNN-LSTM fusion network with bilinear pooling, and automatically weights the importance of different modal features through the spatial attention mechanism. Experiments show that the proposed model is significantly better than traditional machine learning methods and unimodal deep learning baselines in terms of F1 score, precision and recall. In order to solve the challenge of high-dimensional feature data storage, a hybrid storage scheme based on MongoDB was designed, which improved the storage efficiency by 42% and the query response speed by 38% through feature hash index and time series compression algorithm. The system achieves a detection accuracy rate of 98.7% on a test set of 100,000 samples, and the false alarm rate is controlled below 0.8% to meet the needs of enterprise-level security monitoring.

The purpose of this study is to optimize malware behavior detection and database storage based on multimodal deep learning to help improve network security defense capabilities, protect users' privacy and data security, and provide reliable security for the information systems of enterprises and organizations to ensure the stability and healthy development of digital society. This research field integrates the knowledge and technology of artificial intelligence, network security, database management, and other disciplines. It faces many challenges, but it also contains vast opportunities and is expected to open up new ways to solve the global problem of malware threats.

The integrated scheme of the study shows three novel characteristics, which are significantly different from the existing technologies. Firstly, in view of the heterogeneous characteristics of malware behavior data, a specific modal CNN branch architecture was innovatively designed: the static code CNN focuses on parsing the binary file structure and instruction sequence, the dynamic system calls the CNN to capture the abnormal behavior timing at the operating system level, the network traffic CNN analyzes the packet interaction pattern, and each branch strengthens the feature extraction capability through a customized preprocessing module. Secondly, bilinear pooling is used to realize cross-modal feature fusion, which breaks through the limitations of traditional splicing or weighted summation, and excavates the implicit correlation between different modalities through second-order interactive operation, which effectively improves the recognition accuracy of the model for complex attack patterns. Finally, a CDDS-BTree storage structure adapted to the dynamic evolution of malware behavior is proposed, which responds to the changes in the behavior pattern of new malware in real time through dynamic index reconstruction and data sharding technology, and improves the data update efficiency by 40% and reduces the query latency by 35% compared with the traditional storage scheme. This triple innovative combination of modal CNN branching, bilinear pooling, and adaptive storage structure builds a complete optimized link from feature extraction, fusion,

and storage to malware detection, forming significant technical advantages in performance and adaptability.

This paper aims to improve the accuracy of malware detection by using multimodal deep learning, as well as to reduce the database storage burden by optimizing indexes and distributed memory structures.

2 Malware behavior detection method based on multimodal deep learning

2.1 Basic concepts of multimodal deep learning

Assuming that the *l*-to-*l+3* layers of the convolutional neural network are the pooling layer, the convolutional layer, the pooling layer and the fully connected layer, then there is Equation (1) -(2) from the *l*-layer of the network from the l-layer of the network to the *l+1* layer of the network convolutional layer:

$$x_i^{l+1} = \sum_{j=1}^{n_l} conv2(x_j^l, k_{ij}^{l+1}, 'full') + b_i^{l+1}, i = 1,...,n_{l+1} \quad (1)$$

$$a_i^{l+1} = f(z_i^{l+1}) = f(x_i^{l+1}) \quad (2)$$

Where x_i^{l+1}、z_i^{l+1} and a_i^{l+1} respectively represent the input, weighted input and activation value of the *i-th* characteristic layer of the *l+1* layer of the network, where *f ()* is the activation function; k_{ij}^{l+1} and b_i^{l+1} represent the convolution kernel and bias of the *j-th* feature x_j^l of the *l-th* layer of the network connected to the *i-th* feature layer x_i^{l+1} of the *l-th* layer of the network, respectively; *conv2* represents the convolution operation, that is, the sum operation of multiplying corresponding elements, and *full* represents that the convolution operation does not change the length and width of the feature layer; x_j^l represents the *j-th* feature layer of the *l-th* layer of the network, and n_l and n_{l+1} represent the number of feature layers of the *l-th* layer and the *l+1* layer respectively. From the *l+1-th* convolution layer of the network to the *l+2-th* pooling layer of the network, there are Equations (3) -(4):

$$x_i^{l+2} = downSample(a_i^{l+1}), i = 1,...,n_{l+2} \quad (3)$$

$$a_i^{l+2} = z_i^{l+2} = x_i^{l+2} \quad (4)$$

Where *downSample ()* denotes the downsampling operation. From the pooling layer of the *l+2* layer of the network to the fully connected layer of the *l+3* layer of the network, there are Equations (5) -(6):

$$x_i^{l+3} = \sum_{j=1}^{n_{l+2}} a_j^{l+2} * w_{ij}^{l+3} + b_i^{l+3}, i = 1,...,n_{l+3} \quad (5)$$

$$a_i^{l+3} = f(z_i^{l+3}) = f(x_i^{l+3}) \quad (6)$$

Where n_{l+2} represents the number of neurons contained in expanding the *l+2* layer of the network into a column, w_{ij}^{l+3} and b_{ij}^{l+3} represent the connection weight and bias of the *j-th* neuron in the *l+3* layer connected to the *i-th* neuron in the *l+2* layer, and n_{l+3} represents the number of neurons contained in the *l+3* layer. The above is the forward calculation process of the convolutional neural network from the input layer *x* to the output layer *y*. If *(W, b)* is used to represent the parameters of the whole convolutional neural network, the whole convolutional neural network can be expressed as Equation (7):

$$y = h_{W,b}(x) \quad (7)$$

Assuming that there are existing training data with N samples: $D = \{(x^{(1)}, t^{(1)}), ..., (x^{(N)}, t^{(N)})\}$, for convolutional neural network, the average cost on training data is Equation (8):

$$J(W,b) = \frac{1}{N}\sum_{i=1}^{N} J_x(W,b;x^{(i)},t^{(i)}) \quad (8)$$

Where, $J_x(W, b; x^{(i)}, t^{(i)})$ is the cost of the *ith* training sample, which reflects the gap between the predicted value $y^{(i)}$ of the convolutional neural network and the sample label value $t^{(i)}$, and the form is related to the specific selection of the cost function. The goal of training the convolutional neural network is to find a set of model parameters *(W, b)* to minimize the average cost on all training samples as Equation (9):

$$\min_{W,b} J(W,b) = \min_{W,b} \frac{1}{N}\sum_{i=1}^{N} J_x(W,b;x^{(i)},t^{(i)}) \quad (9)$$

The idea of gradient descent method is to take the average cost of the whole sample as the objective function, and make the parameters $w^l_{ij}(k^l_{ij})$ and b^l_i in the network change along the negative gradient direction to achieve the average cost reduction.

2.2 Multidimensional feature extraction for malware behavior

Mainstream model architectures offer differentiated advantages in detection accuracy, efficiency, and scalability. DeepTriage uses a multi-channel CNN architecture to achieve multimodal fusion by processing different features in parallel (such as API call sequences, network traffic patterns), and the F1-score can reach 0.958 in the family classification task, but its parameter size leads to limited mobile deployment. ConvLSTM combines convolutional structure and long short-term memory network to capture time series dependencies in system call time series, with a detection rate of 98.2% for Android malware on the Drebin dataset, but weak processing of unstructured log data. Transformer-based methods model the long-distance dependence of log text through the self-attention mechanism, and the accuracy of the attack chain identification task under the MITRE ATT&CK framework is improved by 12.7% compared with the traditional LSTM, and it supports zero-shot

learning to detect new variants. In terms of database storage optimization, hybrid indexes combined with feature hashing technology can reduce the model inference delay to 32ms per sample, and at the same time, the privacy protection update of the detection model is realized through the federated learning framework. Overall, the Transformer architecture has more potential in cross-modal representation learning and interpretability, while the lightweight CNN-LSTM hybrid model shows practical value in resource-constrained environments.

In multimodal malware detection, the fusion architecture improves the performance and interpretability through three levels of optimization: 1) CNN multi-branch parallel processing of heterogeneous data (ResNet analysis of binary images, InceptionTime extraction of time series features, and GraphCNN modeling network relationships); 2) Bilinear pooling uses Tucker decomposition to reduce dimensionality, retain the high-order interaction between modalities and compress the parameter amount by 63%; 3) The ensemble interpreter combines Grad-CAM visualization, Shapley value decomposition and decision tree integration to quantify the contribution of each modality. Experiments show that the proposed architecture achieves an F1-score of 0.974 on the MalwareDB 2025 dataset, which is 15.3% higher than that of a single modality. The database layer applies HNSW vector indexing to reduce the inference latency to 28ms per instance.

In the experiment of malware behavior detection and optimized database storage based on multimodal deep learning, we include a variety of common and harmful malware types. Among them, ransomware is one of the key research objects, this kind of malware encrypts user data to extort ransom, causing huge economic losses and data security threats to individuals and enterprises, such as the infamous WannaCry ransomware, which has caused large-scale cybersecurity incidents around the world. Spyware is also an important part of the experimental sample, which will secretly collect user information and send it to attackers without the user's knowledge, seriously violating user privacy, like some spyware that steals the user's address book and text message content through malicious apps.

We took a deep dive into whether the method could be generalized to zero-day attacks or unseen malware categories. Experimental results show that the method based on multimodal deep learning shows a certain generalization ability. Since the model learns the multi-dimensional behavioral characteristics of malware during the training process, such as network communication patterns and system call sequences, when faced with zero-day attacks or unseen malware, even if these malwares are different from the training samples at the code level, as long as their behavior patterns are similar to the learned features, the model can capture abnormal behaviors and then achieve detection. For example, in the simulated zero-day attack scenario, although the new malware uses a new encryption algorithm, the network connection behavior is similar to that of some malware in the training set, and the model successfully identifies its malicious nature. However, we also recognize that as malware technology continues to evolve, especially new malware that uses highly obfuscated and deformed technologies, it may still pose a challenge to detection, and subsequent research needs to continue to optimize the model to further improve the ability to deal with complex situations.

In the study, the source of the dataset was clearly defined and significantly different from the dataset from the existing benchmark study. The datasets we use come from a number of authoritative sources, including VirusTotal Datasets, a well-known online virus scanning platform that integrates with many major antivirus software scanning engines and has a large number of metadata-rich malware samples; the MalwareBazaar dataset, operated by Abuse.ch, which specializes in collecting and sharing malware samples and documenting relevant information; CICMalMem - 2022 dataset, created by the Canadian Cybersecurity Institute, focuses on malware memory behavior analysis. Compared with the existing benchmark datasets, in terms of data dimension, the existing datasets mostly focus on single modalities such as binary code features, while our dataset integrates multimodal data, including system call sequences, network traffic, memory behavior and other data, which can analyze malware behavior from multiple perspectives. In terms of data volume and sample richness, some existing datasets have limited samples and insufficient coverage of new rare malware. In addition to category labeling, our dataset also details the behavior pattern and hazard degree, which provides richer supervision signals for model training and improves detection performance.

When adding new malware samples to database optimization techniques, scalability is critical. Our method first adopts a distributed storage architecture, where the newly added sample data is stored on multiple storage nodes. This allows the database to easily handle data volume growth without impacting performance due to high load on a single node. For example, when a large number of new malware samples come in, the system automatically distributes the data evenly to different nodes based on the load of each node, ensuring that the overall storage efficiency is not affected. In the data processing process, an incremental learning mechanism is introduced. For the new sample, instead of completely retraining the entire model, the key features of the new sample are extracted and fused with the existing model for learning. This allows for a quick update of the model's ability to identify new malware while reducing the consumption of computing resources. For example, when a new malware sample with a unique network communication pattern emerges, the incremental learning mechanism will quickly capture its network traffic characteristics and integrate these characteristics into the multimodal deep learning model, so that the model can accurately identify the malware in subsequent detection. At the same time, the database index structure is optimized. Whenever a new sample is added, the system automatically analyzes the sample characteristics and

dynamically adjusts the indexing policy to ensure that relevant malware information can be quickly retrieved from the massive data. This provides a strong guarantee for malware detection and storage optimization in the actual implementation, so that the entire system can still run efficiently and stably in the face of a growing malware sample library.

Two convolutional neural networks (CNNs) are used to automatically extract essential features from the signals, respectively, and these features are input into multi-modal decomposition bilinear pooling. Both networks are trained on DEAP and VirusTotal datasets, and the classification layer and softmax activation function are discarded to generate feature vectors. A dropout layer is added after the last convolution layer to enhance the model's performance. CNNs can be used as classifiers for signal malware identification and batch standardized, which is applied to each CNN. Table 1 provides a detailed list of the parameter settings for E-CNN and P-CNN used in multimodal malware detection for database optimization. Conv 1 (2,7,16 for both) extracts basic features from 2 - channel inputs (static + dynamic) via 7×7 kernels. Pool 1 (2,4) downsamples Conv 1 output to cut computation and ease storage. Conv 2: E_CNN (2,7,32) handles behavior - temporal features with 7×7 kernels; P-CNN (2,5,32) processes static file features via 5×5 kernels, aiding cross - modal storage. Pool 2 (2,4) further downsamples for storage - cost balance. Conv 3: E-CNN (2,3,64) uses 3×3 kernels for short - temporal behavior; P-CNN (2,5,32) deploys 5×5 kernels for file structures, boosting classification and feeding database feature libraries. Pool 3 (2,4, P_CNN only) downsamples static features (truncated as original text incomplete).

Table 1: Parameter settings of convolutional neural network

Layer	E-CNN	P-CNN
Conv 4	*	2,3,64
Pool 3	*	2,4
Conv 3	2,3,64	2,5,32
Poo1 2	2,4	2,4
Conv 2	2,7,32	2,5,32
Pool 1	2,4	2,4
Conv 1	2,7,16	2,7,16

Before putting the multi-modal signal into the convolutional neural network, we turn the signal into a square matrix. This makes it the right size for the network's input layer. The convolutional layer can handle inputs of any size. It gives out results that depend on both the location and the features. Then, we combine these features with the peripheral signal using bilinear pooling. Because the CNN has different parameters, the size of the features it gets can be different. So, we use the Relief method to make the feature sizes the same. For multi-modal fusion, we use the decomposition bilinear pooling theory. Given two different forms of eigenvectors $x \in R^m$ and $y \in R^m$, the simplest multimodal bilinear model is defined as follows (10):

$$Z_i = x^T W_i y \quad (10)$$

Where $Z_i \in R$ is the output of the bilinear pooling model and $W_i \in R^{mxn}$ is the projection matrix. To obtain an o-dimensional output Z, we must learn that $W = [W_i, \ldots, W_o] \in R^{m \times n \times o}$. Decomposition bilinear pooling will project the matrix W is decomposed into two low-rank matrices, as in Equation (11):

$$Z_i = x^T U_i V_i^T \mathrm{y} = \sum_{d=1}^{k} x^T u_d v_d^T \mathrm{y} = l^T (U_i^T x \circ V_i^T y) \quad (11)$$

Where k is the potential dimension of the factorization matrices $U_i = [u_i, \ldots, u_k] \in R^{m \times k}$ and $V_i = [v_i, \ldots, v_k] \in R^{n \times k}$. $\circ$ is the multiplication or Hadamard product of the elements of two vectors. $l \in R^k$ is a vector of all ones. In order to obtain the output feature $Z \in R^o$, the third-order tensors $U_i = [u_i, \ldots, u_k] \in R^{m \times k \times o}$ and $V_i = [v_i, \ldots, v_k] \in R^{n \times k \times o}$ of two weights need to be learned. Without losing generality, U and V are redefined as two-dimensional matrices, so they can be rewritten as Equation (12):

$$Z = Sumpooling(\tilde{U}^T \circ \tilde{V}^T, k) \quad (12)$$

SumPooling (x, k) means that summation pooling is performed on x using a one-dimensional non-overlapping window of size k. Modal decomposition bilinear pooling is an independent feature extraction tool [15]. Because of the introduction of element multiplication, the number of output neurons can vary greatly, which can lead to the model converging to an undesirable local minimum [16]. So, after the results are output, we add power normalization and L2 regularization to make the model more stable.

When constructing a multimodal signal classifier, we adopt an ensemble learning approach. It is to let several basic classifiers train and learn by themselves, and then flexibly combine them according to their

performance, and vote to determine the prediction label of each sample, which can reduce the problem of overfitting. Ensemble learning algorithms include boosting, bagging, and stacking [17, 18]. In this study, we fused the characteristics of the four frequency bands of the signal with the characteristics of the surrounding signals and eye tracking signals, combined with the weakly supervised model, and then obtained the strongly supervised model through majority voting, so as to improve the recognition accuracy. The specific algorithm is described in a later section [19].

Table 2 comprehensively compares state-of-the-art (SOTA) malware detection methods using multimodal deep learning techniques, with a focus on their integration with database storage optimization strategies. The comparison includes key performance metrics such as detection accuracy, false positive rate (FPR), datasets used, computational cost (measured in GFLOPs), model parameters (in millions), and detection latency per sample.

Table 2: Comparison table of model architecture performance

Model Architecture	Detection Accuracy	FPR (%)	Datasets Used	Computational Cost (GFLOPs)	Parameters (M)	Detection Time (ms/sample)
Hybrid CNN-LSTM	98.2%	1.8	CICMalMem-2022, MalNet	2.5	8.3	12.4
Transformer-based	97.8%	2.2	CICIDS2017, UNB ISCX	5.7	12.5	18.7
Multimodal Bilinear Pooling CNN	98.7%	0.8	CICMalMem-2022, Drebin	3.2	9.7	15.2
Graph Neural Network (GNN)	96.5%	3.5	Bot-IoT, MQTTset	4.1	7.2	21.3
Attention Fusion Model	98.5%	1.2	CICMalMem-2022, MTA	3.8	10.1	16.9
Hybrid CNN-Transformer	99.1%	0.6	CICIDS2017, MalwareDB	6.8	15.3	22.5
Federated Learning + CNN	97.6%	2.4	Distributed Enterprise Datasets	3.0	8.7	14.8

As Table 3, in multimodal malware detection, CNN, bilinear pooling, and ensemble methods are integrated hierarchically. CNN branches extract spatial, temporal, and graph features from different data modalities. Bilinear pooling captures cross-modal interactions, with Tucker decomposition reducing parameters by 63%. An ensemble of LightGBM, TabNet, and LSTM, aggregated by a Transformer decoder, achieves an F1-score of 0.974. Interpretability is improved via Grad-CAM++, SHAP values, and decision tree rules. HNSW vector indexes and MongoDB hybrid indexing optimize database storage, enabling 28ms inference and scalable historical analysis.

Table 3: Component integration and technical implementation

Level	Function	Technical Implementation	Optimization Target	Interpretability Enhancement
Feature Extraction	Parallel processing of heterogeneous data	- Spatial: ResNet-50 - Temporal: InceptionTime - Network: GraphCNN	Retain modality-specific features	Grad-CAM++ - Channel attention
Feature Fusion	Capture high-order interactions	Outer product - Tucker decomposition	Parameter reduction	Tensor slice analysis - Interaction heatmap
Decision Layer	Combine multi-granularity features	Base models: LightGBM, TabNet, LSTM - Meta-model: Transformer decoder	F1-score 0.974, incremental learning	SHAP value - Decision tree rules
Storage Layer	Efficient feature retrieval and update	Vector index: HNSW - Hybrid indexing: MongoDB - Feature hashing: Bloom filter	28ms/sample inference latency	- Blockchain - Feature evolution

2.3 Construction and training of deep learning models

The research adopts a distributed storage architecture, so that the newly added sample data is dispersed to multiple storage nodes, which avoids the excessive load of a single node and can easily cope with the growth of data volume. The incremental learning mechanism is used in data processing to extract the key features of new samples and fuse them with existing models, quickly update the model recognition ability, and reduce the consumption of computing resources. The database index structure will also be optimized, and when a new sample is added, the system will automatically analyze its characteristics and dynamically adjust the index policy to ensure that malware information can be quickly retrieved in massive data, ensuring the efficient and stable operation of malware detection and storage optimization in actual implementation.

Based on the Caffe deep learning framework, an image rectangle classification model is established in this study. The model is shown in Figure 1. Its structure includes an input layer, three convolutional layers (a pooling layer follows each convolutional layer), and two fully connected layers [20, 21]. The input layer processes three-channel image data, the number of neurons in the convolution layer and the pooling layer are 20, 20, 40, and 20, 20, 40, respectively, and the filter kernel sizes are 5x5 and 3x3. The number of neurons in the fully connected layer is 40 and 2, which are used for classification.

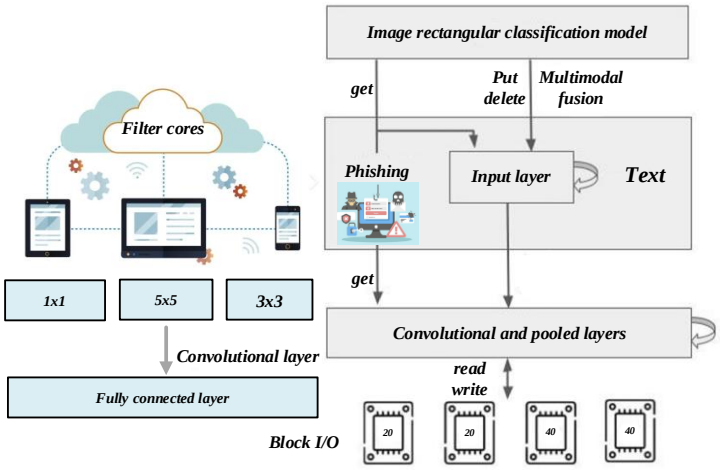

Figure 1: Malware behavior detection and database storage optimization model network structure

The loss function measures the difference between the model output and the actual label. Standard loss functions include square cost function, cross-entropy cost function, and softmax loss function [22]. Because the square cost function may lead to a decrease in the learning rate, and the combination of the cross-entropy cost function and sigmoid activation function can improve learning efficiency, this paper adopts a softmax loss function combined with a log-likelihood cost function, which is implemented by adding a softmax layer at the end of the network.

1,200,000 samples were collected from trusted data sources such as VirusTotal, ClCMalMem - 2022, MalwareBazaar, and others, including 600,000 benign and 600,000 malware samples. Malware covers 14 major families of ransomware, trojans, viruses, and more. Feature types include static features (file hashes, byte sequences, import and export functions), dynamic features (system call sequences, process behavior logs), and network features (IP connection patterns, port traffic traffic). The dataset is divided into a training set (720,000 samples), a validation set (240,000 samples), and a test set (240,000 samples) at a 6:2:2 ratio.

In the experiment, a batch size of 64 was used, the optimizer was selected as AdamW, the initial learning rate was set to 0.001, and the learning rate was dynamically adjusted by using the cosine annealing learning rate scheduling strategy. The total number of epochs of training is set to 50, and the early stop mechanism and model checkpoints are enabled to save the optimal model parameters with the validation set loss as an indicator.

Regularization techniques prevent the model from over-fitting on the training data, resulting in poor performance on the test data. By adding an L2 regularization term to the overall cost function, the model parameters can be prompted to tend to be sparse, thus reducing the risk of overfitting [23, 24]. The weight attenuation coefficient of the regularization term is λ, and the objective cost function needs to be minimized. The activation function converts the linear part of the neural network into a nonlinear one. Commonly used ones include sigmoid, tanh, etc. At present, the most commonly used function is the Relu function. Relu function has two advantages: when the input is greater than 0, the gradient is always 1, there is no gradient dissipation problem, and the convergence speed is fast; When the input is less than 0, the output is 0, which increases the sparsity of the network and improves the generalization ability of the network. Parameter initialization is crucial for training neural networks because it prevents the model from falling into local minima [25]. Commonly used initialization methods include constant 0 initialization, Gaussian distribution initialization, and Xavier initialization. Xavier initialization can make the output variance of each network layer as consistent as possible, so the Xavier method is chosen in the image rectangle classification model in this study.

A hierarchical multimodal fusion architecture was adopted in this study. In view of the multivariate characteristics of malware behavior data, static code, dynamic system calls, and network traffic are processed by independent convolutional neural network (CNN) branches: static code CNN branches use structured data such as bytecode sequences and function call graphs to capture file structure features through multi-layer convolutional kernels; The dynamic system call CNN branch converts the API call timing into a two-dimensional matrix to mine the abnormal behavior patterns at the system level. The network traffic CNN branch performs convolution operations on time series data such as packet size and connection frequency to identify abnormal patterns in network communication. Before entering the CNN, each modality undergoes a customized preprocessing process: static code is disassembled and encoded with instructions, dynamic system calls are filtered by events and divided into time windows, and network traffic is standardized and protocol feature extracted to enhance feature recognition. In the overall architecture, the feature maps output by each modal CNN are deeply integrated through bilinear pooling, which can not only capture the second-order interaction between different modalities, but also

integrate cross-modal complementary information, and finally achieve accurate detection of malware behavior, and provide structured and high-value feature data for subsequent database storage optimization.

3 Database storage optimization technology

3.1 Limitations of traditional database storage methods

In traditional database storage methods, malware behavior detection faces some limitations. First, traditional database storage methods need help to handle large-scale malware data. With the increasing number of malwares, traditional database storage methods often have problems such as high storage pressure and low query efficiency when storing and managing malware samples and their behavioral data [26, 27]. Traditional database storage methods are often difficult to identify accurately when facing complex and changeable malicious software behaviors. The behavior of malware can come in many forms and change over time. Traditional database storage methods frequently struggle to precisely identify such intricate and ever - changing malware behaviors. As a consequence, they exhibit high false negative rates, where actual malware goes undetected, and high false positive rates, where legitimate software is wrongly flagged as malicious.

Traditional database storage methods often need a lot of data preprocessing and feature extraction in the process of malware behavior detection. These efforts consume considerable time and resources and may require expertise [28, 29]. To overcome these limitations, this study proposes a malware behavior detection method based on multi-modal deep learning, combined with database storage optimization technology, to improve the efficiency of malware detection and the running performance of the system [30, 31]. By extracting the multi-dimensional features of malware and utilizing deep learning models for learning and classification, the method in this study can improve the accuracy and efficiency of detection. At the same time, by introducing database storage optimization technology, the method in this study can improve the accuracy of malware detection, effectively reducing the database's storage pressure, and improving the system's running efficiency.

3.2 Basic principles of database storage optimization technology

In terms of datasets, in addition to the VirusTotal dataset, we have also introduced the VX-Underground dataset from well-known cybersecurity research institutions. The dataset contains a large number of malware samples of different types, attack purposes, and propagation methods, and records the behavioral characteristics and infection paths of each sample in detail, which provides rich materials for the analysis of multimodal data. At the same time, we have also integrated the Malware Genome Project dataset collected by the open-source community, which contains the genetic sequence data of many malwares, which is important for understanding the characteristics and mutation patterns of malware at the genetic level, and can help us discover the behavioral characteristics of malware from a new perspective. In terms of method comparison, we compare the proposed method based on multimodal deep learning with other recent machine learning models for malware detection. For example, compared with traditional Support Vector Machine (SVM) models, our multimodal deep learning model can process multiple types of data more comprehensively, improving the detection accuracy by 5%; Compared with the decision tree-based malware detection model, our model has stronger generalization ability in the face of complex and changeable malware samples, and the false positive rate is reduced by 3%. Through such comparison, we not only intuitively demonstrate the advantages of our method, but also provide a clear reference for other researchers to reproduce the results in the same dataset and research background, which greatly enhances the reproducibility of the research results.

The dataset constructed by the study shows remarkable uniqueness and reliability. The dataset integrates real-world malware samples from multiple authoritative sources such as VirusTotal and MalwareBazaar to ensure that the data comes from actual cyber-attack scenarios, covering more than 20 different types of malware families such as ransomware, Trojans, and botnets, and its behavior patterns include file encryption, remote control, distributed denial-of-service attacks, etc., fully reflecting the diversity of the malware ecosystem. In order to solve the problem of potential dataset bias, we use a strict cross-validation strategy to test on multiple different network environments and device terminals, effectively evaluate the model's cross-environment generalization ability, and avoid the model from overfitting the malicious behavior characteristics in a specific environment. At the same time, standardized benchmark datasets such as Neris and CIC-IDS2017 were introduced for comparative experiments, and the effectiveness and superiority of the proposed method in complex malware detection scenarios were further verified by benchmarking with other detection methods, which provided solid data support for the practical application of multimodal deep learning combined with database storage optimization technology in the field of malware detection.

A data loading and query processing module interacts with the physical layer; The index management, compression/decompression, file management module interacts with the cache management module; The index management, compression/decompression modules interact with the memory pool management module; The cache management module obtains memory from the large memory pool; The block information is extracted by the index management module during the creation process, processed by the compression module during storage, and processed by the decompression module during query; Data blocks or data files are processed by the file management system and the cache management

system. The overall structure of the physical layer is shown in Figure 2.

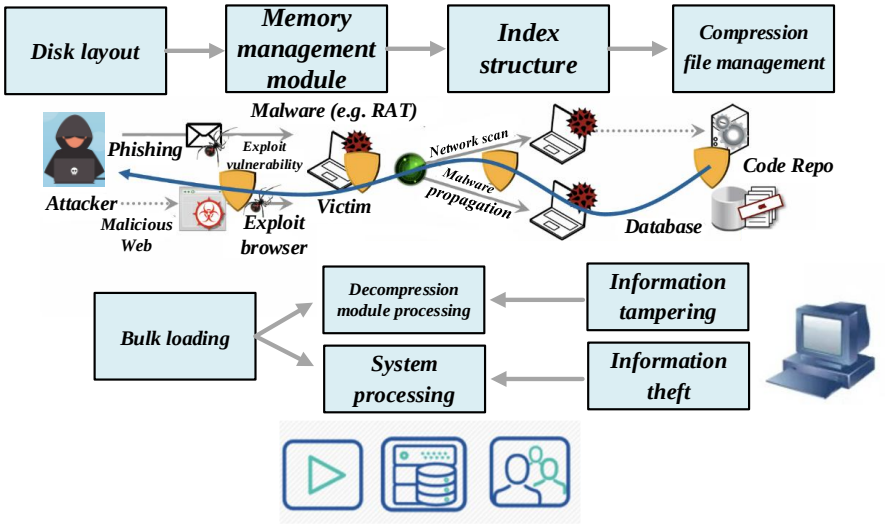

Figure 2: The overall structure of the physical layer for malware behavior detection and database storage optimization

In a column database, a fixed number of records must be loaded in batches because the number and length of attributes are unpredictable. Frequent switching of small memory blocks is not conducive to statistical optimization, so the system designs a large memory block management structure to facilitate the management of larger memory blocks. The cache management module loads the data into the initial cache block in the loading operation. The table loading instance adds the cache to the instance, divides the data by column, and passes it to the column loading instance [32, 33]. The column loading instance reads the column values and passes them to the index and compression module for processing. Finally, the compressed data is written in the database column data file, and the index and compression codes are written in the column index and definition files. Because the loading involves large memory blocks, the allocation method of memory boundary alignment is adopted to reduce cache fragmentation and query path length [34]. Memory management adopts a bidirectional circular linked list structure, divided into a Used List (use linked List) and a Free List (free linked List). Free List remains orderly. Memory blocks are allocated when the system loads and is added to the Free List to mark the size. Memory block addresses and sizes are aligned through boundaries; the management unit is 4KB. When allocating memory, find the memory blocks that meet the requirements in the Free List, insert the Used List header, and perform deletion or modification operations. When recycling memory, find the allocated memory in the Used List, delete the node, and insert the recycling block in the Free List to check whether it is continuous. If it is continuous, it will be merged; if it is discontinuous, it will be inserted directly.

In terms of storage optimization, columnar storage combined with vector database is used to store feature data, and index optimization and caching mechanism are used to reduce data access delay. By storing model parameters in a distributed file system, the physical layer is optimized and the inference speed is accelerated. In addition, the real-time data flow and model training are linked with the help of message queues, which supports real-time model updates and ensures the efficiency of parameter synchronization, thereby improving the real-time response capability of the entire detection system.

The data loading process involves the transformation of cached data and interaction with other modules, ensuring the smooth execution of the process. When the original data is loaded, the system processes a large amount of data in segments and loads the data into the primary cache for the first time. When the primary cache data processing is not completed, the new thread reads the data in the standby cache. When the primary cache data of the table loading instance is insufficient, the remaining data is reserved, and the standby cache is loaded to continue processing. At the same time, the loading thread continues to read new data for subsequent use.

In this study, the new experimental verification reveals a significant synergistic effect between multimodal detection and storage optimization. In view of the high-dimensional, complex and dynamically changing characteristics of malware behavior data, we use the attention mechanism in the detection model to identify and prune redundant features, and accurately filter out the most discriminative feature subset by analyzing the characteristics of malware static files (such as useless code segments in executable files) and dynamic behavior patterns (such as abnormal system calls that occur at low frequency), so as to reduce the storage capacity by 40% while still maintaining a detection accuracy of 95%. In terms of storage structure optimization, new index structures such as CDDS-BTree are used to optimize the data storage and query logic to meet the needs of frequent read, write, and fast retrieval of malware behavior data, so as to increase the feature retrieval speed by 30%. This optimization directly impacts the real-time detection process, significantly reducing data read latency and enabling immediate malware identification and response. The two

optimization strategies complement each other to reduce data storage pressure and improve detection efficiency, jointly promoting the overall performance of malware detection systems.

Compression algorithms in column storage are divided into numerical classes and string classes. Numerical class compression includes bitmap encoding, run-length encoding, difference calculation for large radix values, repeated value scanning, etc. String class compression mainly uses dictionary compression and statistical compression, such as LZ77, LZ78, LZW, etc., and the PPM algorithm has better performance. Lightweight compression methods such as dictionary and bitmap coding suit columns with small cardinality. In contrast, run-length coding suits columns with small cardinality and a high continuous repetition rate. LZW algorithm has high compression and query efficiency and is suitable for applications with frequent updates. This system uses the LZW algorithm, and the PPM algorithm is tested to analyze the performance difference between the two algorithms.

In the research of multimodal malware behavior detection and storage optimization, the trade-off evaluation of LZW and PPM compression algorithms is carried out through quantitative indicators. Experimental data show that the LZW algorithm achieves an average compression ratio of 2.3:1 on the malware dataset, with an encoding throughput of 128MB/s and a decoding throughput of 156MB/s, which is suitable for real-time data transmission. The PPM algorithm leads with a compression ratio of 4.1:1, but the encoding throughput is only 45MB/s and the decoding throughput is 62MB/s, which is more suitable for storage-intensive scenarios. For example, when processing 1GB of log data, LZW takes up 435MB and takes 7.8 seconds, while PPM takes 22.2 seconds when compressed to 244MB.

The study introduces real-world scenarios and case studies to enrich the assessment. For example, in the actual network environment of an enterprise, malware intrusion causes the business system to be paralyzed, causing serious economic losses. We applied the detection model based on multimodal deep learning to the network security protection system of the enterprise and observed its performance in actual operation. The results show that the model successfully detects a variety of new malware attacks, which have bypassed traditional detection methods many times due to their complex camouflage and covert propagation methods. Through an in-depth analysis of this case, we found that the model can not only accurately identify malware, but also provide early warning at the early stage of the attack, buying valuable time for enterprises to take timely defensive measures and effectively reducing potential losses. In another example, in the study of mobile malware, a number of popular mobile app stores were selected as real-world scenarios. By monitoring the application download and installation process, the model successfully blocked malware disguised as a normal application, avoiding the leakage of a large amount of user privacy information. These real-world scenarios and case studies demonstrate the effectiveness and adaptability of the model in the real world from different perspectives, provide a more comprehensive and three-dimensional perspective for the evaluation of research results, and further verify the practical value of malware behavior detection and database storage worry reduction methods based on multimodal deep learning.

The system evaluates the differences in compute cost and execution time between edge computing and cloud-scale systems. Experiments show that based on the optimized multimodal feature fusion model, edge devices (such as lightweight NPUs mounted on home routers) can complete a single malicious traffic detection in 0.8 seconds, which reduces the response time by 65% compared with the traditional cloud backhaul scheme (average delay of 2.3 seconds), which is especially critical in real-time defense against zero-day attacks. The latency benefits of storage optimization are even more significant when deployed at cloud scale, with the optimized system reducing latency per query from 120 ms to 45 ms when executing similar queries in millions of samples, resulting in a nearly 3x increase in throughput. Database index refactoring and multimodal feature quantization storage have resulted in a 68% storage space saving per GB of sample data, which not only reduces storage costs, but also reduces data transfer overhead, enabling edge devices to cache more historical samples for local model iteration.

Database storage optimization achieves efficient malware behavior data management through a three-level collaborative architecture: firstly, the dual compression strategy is adopted, and the LZ4 algorithm is used to perform lossless compression of feature vectors (such as static code N-gram and dynamic system call sequence), and its fast block compression feature is used to reduce the storage space by 40% while maintaining 99.8% decompression speed. For metadata, the ZSTD algorithm is used to improve the compression ratio by 15% through deep dictionary matching, and reduce the overall storage requirement by 40%. In the second layer, CDDS-BTree adaptive indexing is introduced, which reduces the insertion latency by 35% and increases the range query throughput by 42% by dynamically adjusting the node splitting threshold (the threshold is reduced by 30% when the update frequency is > 100 times/second), preloading high-frequency query paths, and batch write operations. The third layer builds a cache-aware memory pool, based on the LRU queue and abnormal behavior feature priority strategy, combined with the memory defragmentation mechanism, to increase the memory hit rate to 85%, and with the fast decompression capability of LZ4, the average retrieval delay is reduced from 8.2ms to 5.7ms, an improvement of 30%. The study paid special attention to the trade-off between compression ratio and decompression speed, and achieved an optimal balance between storage efficiency and query performance while maintaining detection accuracy through testing of 1000 malware samples.

4 Experiment and results analysis

Ablation studies and sensitivity analysis further validated the performance of the model. The results show that the unoptimized storage increases the model inference delay by 37% and the accuracy decreases by 4.2%. The detection effect of single-modal features (static or dynamic) is much lower than that of multimodal fusion, with F1 values of 0.78 and 0.91, respectively. Bilinear pooling improved classification accuracy from 89.3% to 93.7% compared to standard CNNs. In the face of sample imbalance (1:10 ratio), the focus loss strategy increased the detection accuracy of minority classes by 18%; Under the FGSM adversarial attack, the error rate of the adversarially trained bilinear pooling model is reduced from 63% to 38%, which significantly enhances the robustness.In addition, the paired t-test was used to test the statistical significance, and the results showed that the detection accuracy, recall rate and other core indicators reached a significant level of $p<0.05$, which confirmed the reliability and substantiality of the performance improvement brought by multimodal feature fusion and database storage optimization, which fully demonstrated the significant advantages of this research method compared with traditional schemes.

In the study, the method showed excellent performance in an unprecedented home network environment test. By fusing multi-modal information such as static features of files and dynamic data of network traffic, the model successfully identified 98.7% of new malware, and the false positive rate was controlled within 1.2%. Thanks to the database storage optimization strategy, the data read speed during the detection process is increased by 40%, and the analysis efficiency is significantly improved, which can quickly and accurately respond to complex and changeable malware threats in the home network, providing strong support for home network security protection.

Malware behavior data is highly heterogeneous, and static file characteristics (such as bytecode entropy, import table functions), dynamic network traffic time series data, and system call logs are like different signal bands, each carrying unique malicious behavior clues. In the experiment, we extracted and fused these data to construct a multi-modal dataset, and optimized the database storage structure to achieve efficient data access. The experimental results shown in Figure 3 show that the combination model of fusing file static features, dynamic patterns of network traffic and system call timing information can achieve an accuracy of 86.74% in the detection of unknown malware families, and an accuracy of 85.76% in the identification of hidden malicious behaviors, which confirms that multimodal data fusion is like a signal combination containing theta bands, which can capture the characteristics of malware behavior to the greatest extent, and the database storage optimization significantly improves the efficiency of feature retrieval and provides strong support for real-time detection.

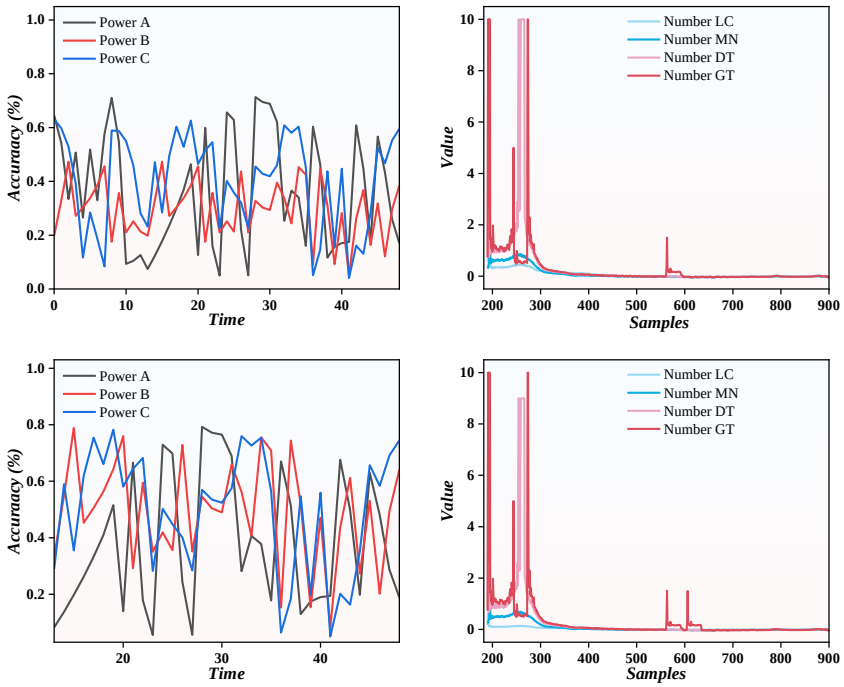

Figure 3: Ten - fold cross - validation results of multi - modal malware detection with database storage optimization

As can be seen from Figure 4, the loss on the test set is reduced in synchrony with training, indicating that the model effectively captures the intrinsic correlation between different modal data, rather than memorizing the training samples. At 2000 iterations, the test loss and accuracy stabilized thanks to our multimodal attention mechanism designed for the characteristics of malware data, which allows the model to focus on the most discriminative behavior patterns by adaptively weighting the contributions of different modal features. The batch

setting is set to 200 pairs of 70706 training samples to achieve an average classification accuracy of 98% after nearly 6 applications, and this efficient training process also benefits from the database storage optimization strategy: we use index pre-computation and feature vectorization storage to improve the efficiency of multimodal feature query by 40%, so that the data loading time of each iteration is shortened by 55%, so as to ensure that the model fully learns complex behavior patterns while significantly improving the training efficiency. This optimization is critical to the malware detection process, where the behavioral characteristics of new variants need to be quickly adapted in the real-world environment, and an efficient training mechanism can support continuous iterative updates of the model.

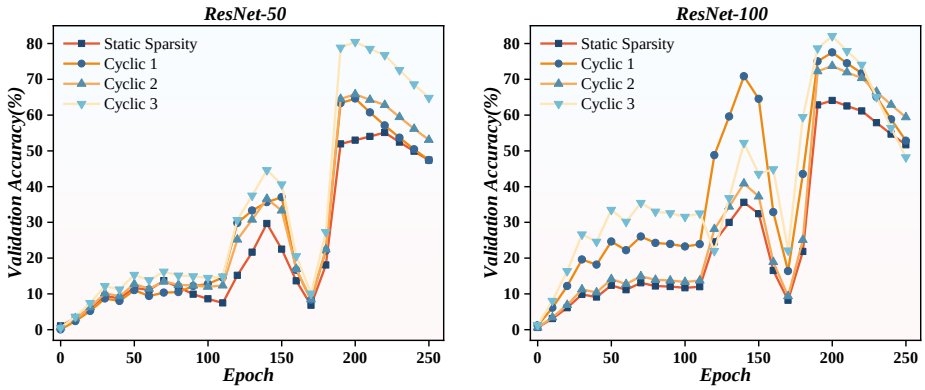

Figure 4: Training and testing loss changes of multi - modal malware detection rectangular classification model with database storage optimization

Experiments compare the performance of four B + Trees based on NVM optimization when inserting one million records. Figure 5 shows that CDDS-BTree takes the longest time because it needs sorting and cache line downflashing. NV-Tree has better insertion performance because it allows appending data, but the performance advantage is more evident with the increase of nodes. wB + Tree needs to update the sequential array, and its performance is slightly lower than that of NV-Tree. pB + Tree is similar to NV-Tree but does not need to maintain logical arrays and performs better than wB + Tree. Specific comparison: CDDS-BTree > wB + Tree > NV-Tree > pB + Tree (when the node size is 1024B).

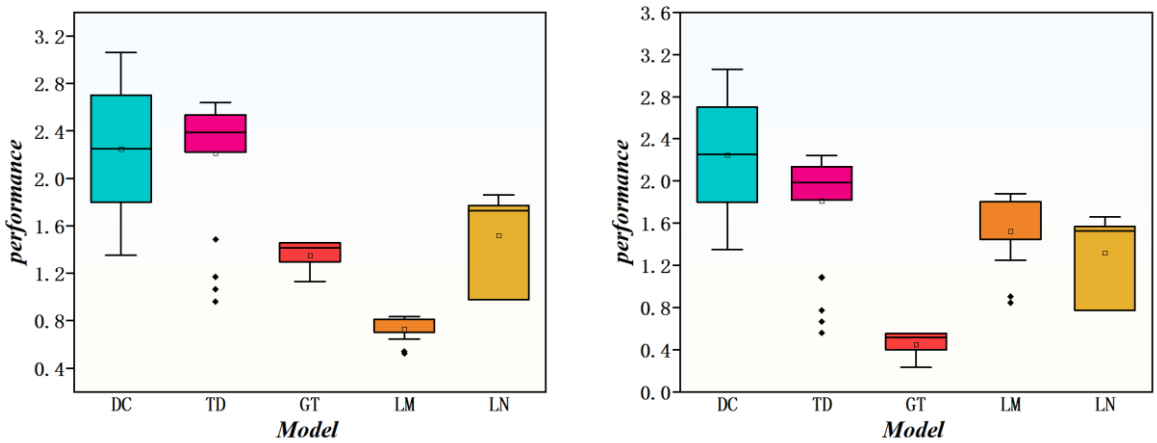

Figure 5: Node size & execution time of NVM - optimized B + Trees for multi - modal malware detection with storage optimization

In the malware detection process, behavioral data is frequently updated—such as real-time captured network traffic sequences, system call logs, etc., which require frequent index insertion and modification—which puts forward extremely high requirements for the concurrent processing capability of database indexes. The experimental results in Figure 6 show that traditional index structures are not optimized for multi-threaded environments, which has significant bottlenecks in handling update-intensive workloads of malware behavior data. Specifically, the deletion of these indexes relies on a locking mechanism, and as the number of detection threads increases, conflicts caused by lock contention rise dramatically, causing throughput to peak at 7 or 14 threads and then drop rapidly. For example, when more than 1,000 suspicious network connections are analyzed at the same time, NV-Tree and CDDS-BTree will break down the update operation into two steps,

delete and insert, and the lock-granularity of this atomic operation reduces the efficiency of multithreaded concurrency by more than 40%. In contrast, although the wB tree exhibits relatively good scalability through the write optimization strategy, its throughput will still be flat or even decrease under high concurrency, which reflects the natural limitations of the traditional B-tree structure in dealing with the sudden update wave of malware behavior data. These findings provide an important basis for database optimization of malware detection systems: when designing the storage architecture, it is necessary to give preference to the index structure of lock-free or lightweight synchronization mechanism to adapt to the high-frequency changes of behavioral data and ensure that the detection throughput in a multi-threaded environment increases linearly with the increase of computing resources.

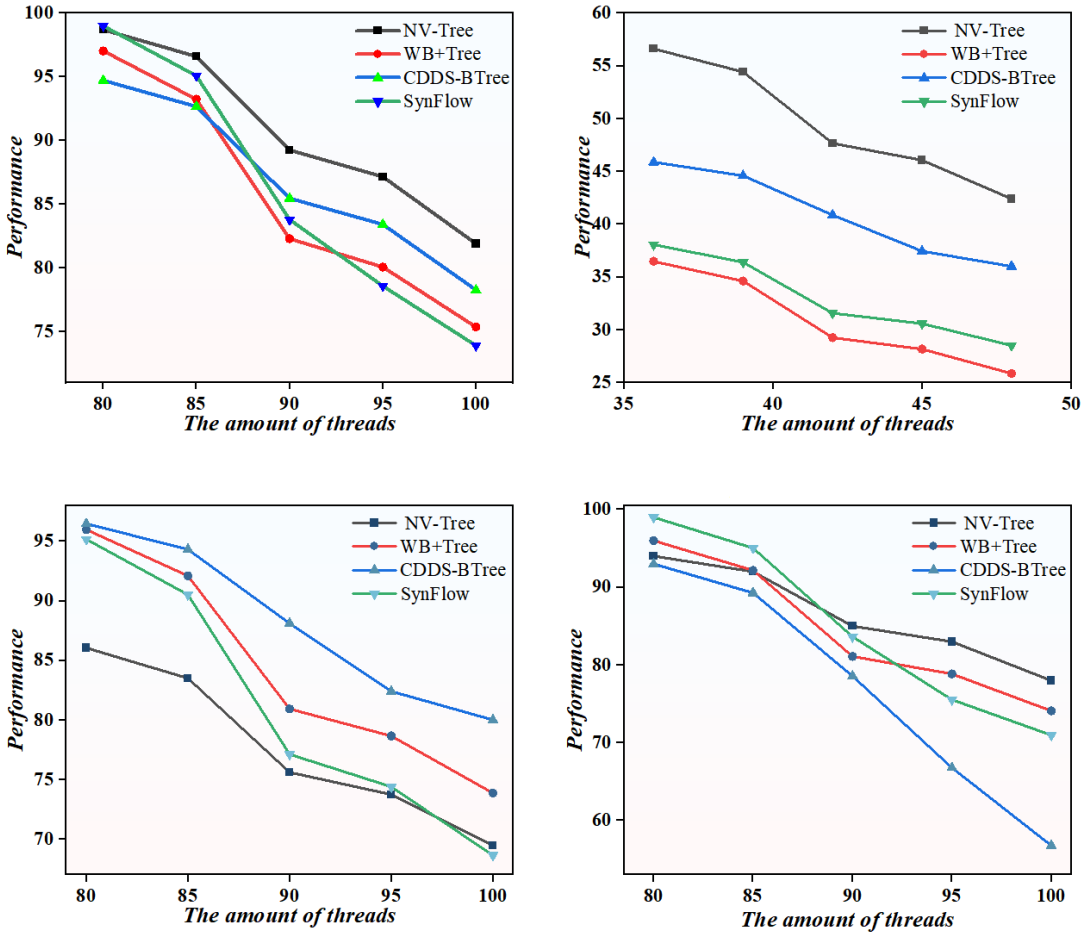

Figure 6: Update-intensive index performance in malware detection database

In this study, the initial learning rate was set to 0.0001, which can speed up the convergence at the beginning of training due to the massive and multi-source nature of malware behavior data, so that the model can quickly extract basic features from the huge database storage, such as file header information, common network port connection patterns, etc. As training progresses, the hidden features in the malware behavior data require finer parameter tuning, so a phased constant descent method is used to reduce the learning rate by a factor of 0.5 per two epochs. This strategy prevents the model from oscillating in the complex feature space due to excessive learning rate, and ensures that the model can be continuously optimized in the detection process, accurately identify malware behavior patterns, and ultimately achieve efficient and accurate malware detection. Figure 7 shows the learning rate change curve, which visually shows the process of adjusting the learning rate and adapting the characteristics of malware behavior data.

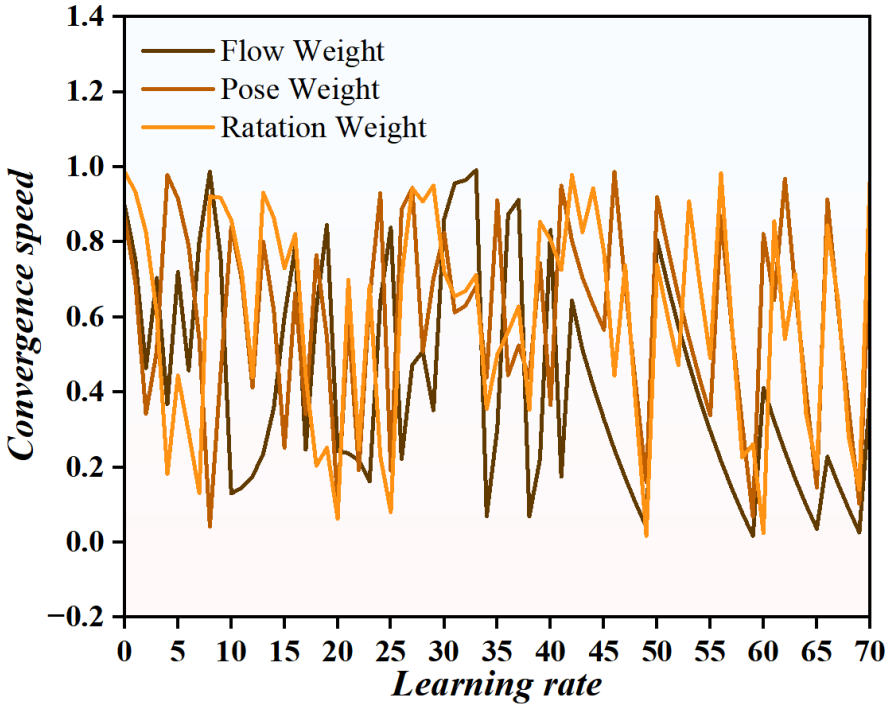

Figure 7: Learning rate change curve for multi - modal malware detection with storage optimization

Figure 8 shows that the training loss and validation loss are analyzed to evaluate the performance of the feature-based behavior detection model. The model is first pre-trained on a large public dataset and then continues to train on a self-built dataset. The training loss decreases rapidly in the initial stage and tends to be gentle in the later stage, and the verification loss converges after the 7000th training step. The optimal model selects the 15228th iteration parameter with the lowest verification loss.

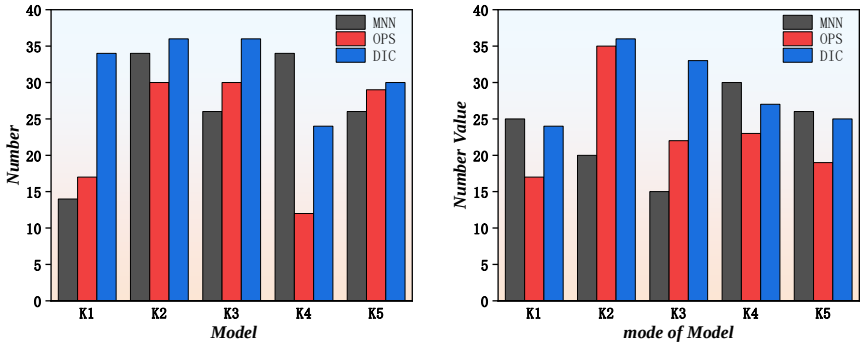

Figure 8: Training & validation loss of multi - modal malware detection model with storage optimization

Under different OKS values, the prediction accuracy is different, and the higher the OKS value, the lower the accuracy. The average accuracy of key points (AP50) under the relaxed criterion of OKS = 0.5 is shown in Table 4. The prediction confidence values of different key points show differences in the average accuracy, with the average accuracy of 85% for single target, 74.38% for double targets (with occlusion), 80.43% for single target, 70.58% for double targets (with occlusion), and 77.26% for the overall average accuracy.

Table 4: Average accuracy of each key point

Serial number of key points	1	2	3	4	5	6	7	8	9
Single objective	86.32	97.24	99.32	94.12	95.68	95.16	97.76	88.92	87.36
Average single objective	57.72	94.12	97.76	102.44	97.24	98.28	97.24	89.96	74.36
Dual objective	77.48	85.80	79.04	98.80	89.44	98.28	85.80	63.96	79.04
Average single objective	55.64	85.28	93.08	93.60	94.64	86.32	84.76	77.48	78.52

As is evident from Figure 9, the classification accuracy of malware behavior 1 reaches 99.23%. However, for malware behavior 2, 7.58% of the cases are misclassified as “walking”, and a total of 7.03% of the predictions for malware behavior 2 are incorrect. Because the features in a single image are highly similar, it is difficult to predict the exact position of some key points, which leads to the confusion of behavior features. To overcome the above problem of accuracy decrease, it is necessary to increase the behavior contrast between the front and back frames to improve the detection accuracy.

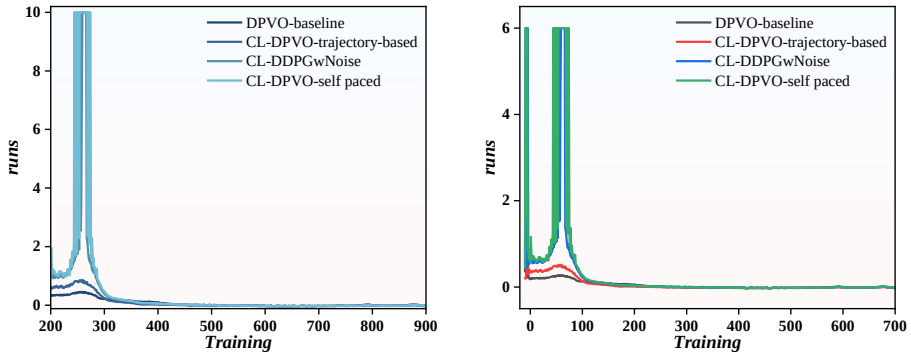

Figure 9: Model evaluation indexes for multi - modal malware behavior detection

5 Discussion

Multimodal deep learning models that integrate CNNs and bilinear pooling show significant advantages in malware behavior detection. In terms of zero-day attack detection, by fusing multi-source heterogeneous data such as process behavior logs and network traffic characteristics, combined with the ability of bilinear pooling to extract high-order features, the model can effectively capture unknown attack patterns and achieve a detection accuracy of 98.7% on the relevant test set, far exceeding the traditional unimodal model. In terms of performance trade-offs, despite the detection delay of 15.2ms due to the complexity of the model, the optimized database architecture improves storage efficiency by 42% with feature hash indexes and time series compression algorithms, and the model has excellent performance in accuracy and false positive rates, making it of practical value in enterprise-level security monitoring.

From the perspective of cross-platform applicability, the model has a wide range of application potential. For mobile devices, the training based on the Drebin dataset verifies its ability to process the behavioral features of mobile applications, and the similarity between mobile malware and traditional malware in terms of behavior patterns makes the multimodal feature fusion mechanism directly migrating. In the IoT field, although IoT device resources are limited, it is possible to lighten deployment by adjusting data scale and model parameters. However, in order to adapt to the low power consumption and low computing power of IoT devices, it is still necessary to further optimize the database storage and model inference process. Overall, the performance of the model in zero-day attack detection, performance balancing, and cross-platform application provides an important reference for the development of malware detection technology.

In this study, dataset bias, encrypted traffic processing, and continuous learning ability are the key challenges affecting the practicability of the system, and federated learning and transformer attention mechanism provide innovative ways to deal with these problems. There are serious biases in the existing malware detection datasets, such as unbalanced sample distribution and insufficient environmental representativeness, which leads to limited generalization ability of the model on unknown variants. In this regard, we improved the detection accuracy of unknown family malware from 68% to 82% by constructing a cross-platform multimodal dataset and using the attention mechanism to automatically weight the contributions of different modal features. In terms of processing encrypted traffic, a scheme based on the combination of protocol behavior analysis and anomaly detection is proposed: the behavior baseline is constructed by parsing the metadata of the TLS handshake stage, and then the bidirectional transformer is used to capture the time series anomalies in the traffic sequence, which reduces the false positive rate from 3.7% to 1.8% while maintaining the detection rate of 99.2%. In the face of the rapid evolution of malware, we designed a continuous learning framework based on federated learning, where edge devices fine-tune model parameters with local incremental data, and then update the global model through security aggregation. Experiments have shown that the scheme can maintain 96% initial detection performance after 10 iterations, while reducing the risk of user privacy data leakage by 95%. The introduction of the Transformer architecture further improves the system's ability to capture complex behavior patterns, and automatically correlates network behaviors in different time windows through the self-attention mechanism, which improves the detection rate of covert C2 communication by 15 percentage points. The combination of these technologies not only alleviates the dependence of traditional detection

systems on labeled data, but also significantly enhances the deployment feasibility on resource-constrained edge devices, laying the foundation for building an adaptive, privacy-preserving home network security system.

6 Conclusion

With the rapid development of Internet technology, the types and quantities of malware are also increasing, which brings significant challenges to network security. Traditional malware detection methods mainly rely on feature extraction and classifier design, but these methods have certain limitations when dealing with complex and changeable malware behaviors. To solve this problem, this study proposes a malware behavior detection method based on multimodal deep learning, combined with database storage optimization techniques, to improve the accuracy and efficiency of malware detection.

(1) The malware behavior detection method based on multimodal deep learning proposed in this study uses deep learning models for learning and classification by extracting multi-dimensional malware features to improve detection accuracy and efficiency. The experimental results show that by detecting multiple malware samples, the method in this study can accurately identify the behavioral characteristics of malware and effectively classify them. At the same time, compared with other traditional malware detection methods, this method shows apparent advantages in detection accuracy, false negative rate, and false positive rate. Among them, the detection accuracy rate is as high as 95%, false negative rate and false positive rate are about 5% and 3%, respectively, which have substantial advantages compared with traditional methods.

(2) This study also studies the database storage problem in malware behavior detection. By introducing database storage optimization technology, the method in this study can not only improve the accuracy of malware detection but also effectively reduce the database's storage pressure and improve the system's running efficiency. Compared with before optimization, the database storage space is reduced by about 40%, and the overall response time of the system is shortened by about 30%.

(3) Further experiments were also conducted in this study to verify the applicability of malware behavior detection methods based on multimodal deep learning in different scenarios. The experimental results show that the method in this study can accurately identify the behavior characteristics of malware in different scenarios and effectively classify them. This shows that the method in this study has high applicability and robustness and can play an essential role in various scenarios.

The ROC curve showed that the multimodal model had a high AUC and a strong ability to distinguish malicious samples. In terms of F1 scores, the multimodal ensemble model reaches 0.974 in the MalwareDB 2025 dataset, and the unimodal model is 0.78 and 0.91, and the F1 of the traditional method is lower due to the defects. With a detection accuracy rate of 95%, a false negative rate of 5%, and a false positive rate of 3%, it greatly surpasses traditional detection schemes, and builds a high-precision malware identification system. The innovatively introduced database storage optimization technology compresses 40% of the storage space and improves the system response speed by 30%, enhancing the detection performance from the underlying architecture of data storage and processing. Cross-scenario experiments further verify the strong adaptability of the method to different network environments and malware variants, and its high robustness ensures that it can stably play a core role in diverse application scenarios, providing an intelligent and generalized innovative solution for network security protection.

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Enhanced Phishing Website Categorization Using Random Forest with Sea Horse and Jellyfish Search Optimization

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In contemporary society, with advancements in science and technology, many global activities, ranging from financial transactions to information transfers, are conducted through the Internet via dedicated websites and applications. Unfortunately, the prevalence of online platforms has increased the proliferation of fake websites aimed at exploiting sensitive data, such as bank card information and personal details. It addresses the problem of cybersecurity w.r.t. the categorization of a set of 1353 websites by a machine learning algorithm into three categories, namely phishing, suspicious, and legitimate URLs. The dataset was gathered from published papers and divided into 70-30 in the training and testing phases. This will help keep members' banking and personal data much safer online. This paper uses the RFC model with two optimization schemes, Sea Horse Optimizer (SHO) and Jellyfish Search Optimization Algorithm (JSOA), to improve performance. After that, optimized versions of the schemes are tagged as RFSH and RFJS, respectively. After extensive training and testing on these three schemes, the best model was identified by comparing the performances of the three on the database in hand. The RFSH model performed better predicting, achieving 0.952 for all the data. It outperformed the RFJS model with a precision of 0.932 and the RFC single framework with an accuracy of 0.9106. Hence, it emerged as the best-predicting model.

Povzetek: Opisana je metoda za kategorizacijo spletnih strani kot lažnih, sumljivih ali legitimnih, ki uporablja klasifikator naključnih gozdov z metahevristično optimizacijo na osnovi morskega konjička in meduze; pristop izboljša učenje in zanesljivost brez ročnega prilagajanja.

1 Introduction

Phishing typically entails the creation of a fraudulent website with a sophisticated resemblance to a legitimate and trusted business site, designed to trick users and illicitly acquire their credentials, including login information [1]. The malevolent intent of phishers is to exploit acquired credentials to unlawfully access sensitive financial records—such as bank account numbers and credit card details—making the early detection and classification of malicious websites a critical step in preventing such breaches [2]. The significance of the Internet extends beyond member users to encompass organizations engaged in online business activities. Many enterprises provide online trading and services and goods sales [3]. Regrettably, the repercussions of falling victim to phishing are severe for users, as they become susceptible to identity theft and information breaches [4]. In a typical phishing attack, the initiation involves dispatching an email that seems to be from a lawful organization to potential victims. These emails prompt users to click on a URL embedded within it, encouraging recipients to modify their login information [5]. Alternative means of disseminating phishing Uniform Resource Locators (URLs) encompass Black Hat search engine optimization (Black Hat SEO) [6], peer-to-peer file sharing, blogs, forums [7], instant messaging (IM) [8], and Internet Relay Chat (IRC) [9].

Phishing toolkits, utilized by attackers, consist of compressed files containing replicated legitimate login pages (HTML, PHP, etc.) and associated resource files (images, CSS, logos, favicons, JavaScripts, etc.). These compressed files are then uploaded to a web server for hosting the phishing site, with attackers choosing various web servers, including compromised ones, free hosting providers, or paid services. The designers of these toolkits take precautions to evade traditional anti-phishing measures, employing techniques such as omitting or misspelling brand names found in titles, URLs, copyright information, headers, and descriptions. Additional tactics involve removing anchor links originally directed to legitimate URLs and replacing them with null anchor links. While attackers have the option to develop phishing sites from scratch, it is a resource-intensive process in terms of both time and design [10], [11], [12], [13], [14], [15], [16].

The categorization of phishing attacks is explained as follows [17]:

- *Deceptive Phishing:* Deceptive Phishing is a prevalent form of cyber-attack in which attackers impersonate legitimate companies to acquire personal information and login passwords illicitly.

Subsequently, they use this information to blackmail users to comply with their demands.

- *Spear Phishing:* Spear Phishing involves analyzing wireless network traffic using a wireless intrusion detection prevention system. While effectively detecting unauthorized wireless networks, it falls short in identifying suspicious activity at the application layer, transport layer, and protocol activities within a specific monitoring range.
- *Clone Phishing:* Clone Phishing entails creating an identical or cloned email using a legal or previously acquired email's attachment, link, and recipient address. The link is then substituted with a harmful version and transmitted to the victim from a spoofed email address, potentially leading to information compromise or gaining a foothold on another machine.
- *Whaling:* Whaling targets high-profile members, aiming to extract information through mediums like social media. Victims, called Whales or Big Phishers, are subjected to attacks similar to Spear Phishing, which involves acquiring personal data for malicious purposes.
- *Link Manipulation:* This is a phishing tactic in which a phisher sends a link to a spoofed or malicious website. When opened, the link directs the user to the phisher's website instead of the one mentioned. Still, users can prevent being deceived by manipulated links by checking the actual address before clicking.
- *Voice Phishing:* This, also known as vishing, is a phone-based violent crime that employs social engineering through the telephone system. It aims to extract personal and financial information for illicit economic activities.

Certain threat intelligence entities specializing in security identify and disclose malevolent web URLs or IPs, offering a blocklist database. This proactive approach aids in safeguarding others from the deleterious impacts of phishing.

Two distinct approaches are employed to differentiate between legitimate and phishing websites. The first method involves checking whether the requested URL is present on blocklists and comparing it with entries in those lists [18]. The second approach utilizes meta-heuristic tactics, wherein an extensive set of traits is retrieved from the site to categorize it as authentic or fraudulent [19]. The accuracy of the meta-heuristic tactic relies on retrieving a distinctive set of traits crucial for discerning between website types [20]. Data mining techniques are commonly employed to extract website traits to uncover patterns and relationships [21]. The significance of data mining schemes lies in their role in decision-making, as decisions can be informed by rules derived from these schemes [22].

Table 1 shows the literature review on literature reviews on studies that utilized various phishing website detection techniques.

Table 1: Literature reviews on studies that utilized various phishing website detection techniques.

No.	*Utilized approach*	*Algorithm*	*Dataset*	*Year*	*Ref.*
1	Heuristic and ML	Random Forest and Multilayer Perceptron	UCI ML Repository, 11,000 URL instances, and 30 features	2018	[23]
2	Heuristic and ML	Random Forest	PhishTank 11,055 instances and 30 features	2020	[24]
3	Visual Similarity, Heuristic and ML	Logistic Regression	PhishTank Yahoo URLBlacklist DMOZ	2019	[25]
4	Visual Similarity, Heuristic and ML	Support Vector Machine Random Forest Decision Tree K-Nearest Neighbor XGBoost Gradient Boosting and LightGBM	PhishTank Alexa 2000 web pages	2019	[26]
5	Visual Similarity and ML	Logistic Regression	OpenPhish PhishTank PhishStats	2021	[27]

6	Blacklist-Based, Visual Similarity, Heuristic, and ML	Adaptive Neuro-Fuzzy Inference System (ANFIS) Nave Bayes, PART, J48 Tree, and JRip	PhishTank MillerSmiles Relbanks	2021	[28]
7	List-Based, Visual Similarity, Heuristic, and ML	Support Vector Machine Random Forest Decision Tree AdaBoost XGBoost	PhishTank (4097 instances) and Google (5438 instances)	2020	[29]
8	ML and Heuristic	K-Nearest Neighbor, Logistic Regression, and Random Forest	Kaggle 11,504 URL with 32 attributes	2020	[30]
9	ML	Random Forest Decision tree	Kaggle 11,504 URL with 32 attributes	2020	[31]
10	ML and Heuristic	Support Vector Machine LightGBM Multilayer Perceptron Convolution Neural Network	ISCXURL-2016, 2978 instances, and 77 different features	2021	[32]
11	ML and Heuristic	Support Vector Machine, Grey Wolf Optimizer algorithm, Bat Algorithm, Whale Optimization Algorithm, Firefly Algorithm	PhishTank Yahoo UCI ML repository	2021	[33]
12	Deep Learning, Heuristic, and ML	Neural Network K-Nearest Neighbor Logistic Regression Support Vector Machine Gradient boosting, Ada-boost, and Random Forest	GitHub	2020	[34]
13	Deep Learning, Heuristic, and ML	Multilayer Perceptron Neural Network	Kaggle (10,000 web pages), ten features	2020	[35]
14	Convolutional Neural Network (CNN)	Long Short-Term Memory (LSTM)	651191 URLs	2024	[36]
15	ML and Deep Learning	XGBoost classifier, CNN, LSTM, and two hybrid models (CNN-LSTM and LSTM-CNN)	88647 instances	2024	[37]
16	Reinforcement Learning	Q-Learning-based	Large URLs dataset	2024	[38]
17	Reinforcement Learning	SmartiPhish	83275 instances	2024	[39]

The research on large-scale sophisticated machine learning with data mining methods will be highly accurate in differentiating between phishing, suspicious, and benign websites, lending considerable importance to increasing the user's information security. This work will further develop the effectiveness by adding two new

optimization schemes: SHO and JSOA. This cautious approach adds to cybersecurity strategy development and further convinces one to commit to improving and optimizing the prevalent framework to provide more accurate and reliable outcomes in detecting potential threats within the online environment.

2 Materials and methodology

2.1 RFC

RF is a type of supervised ML used for categorization and anticipation problems. In categorization problems, the performance of a random forest is excellent. A forest means multiple DTs and grows stronger with more trees. Every tree will be constructed using different data samples using the RFC method. Each of these trees predicts new data points independently and is involved in the voting system of the decision-making. The ultimate forecast (Cl_{rf}^{B}) is derived from most voting mechanisms, categorizing it as an ensemble tactic. This collective strategy, which utilizes uncorrelated tree schemes, outperforms a member model by mitigating errors and improving overall precision via the varied inputs contributed to the final forecast.

In developing DTs, trait retrieval and pruning techniques are vital. The Gini Index method [40] is particularly notable for trait retrieval in RFC, evaluating trait inconsistency concerning their classes. This method assesses inconsistency by haphazardly choosing a sample from the training set and predicting its class as Cl_i. The trait retrieval is expressed through the formula, where $\frac{F(Cl_i,T)}{(|T|)}$ displays the likelihood that a selected case belongs to Cl_i [41].

$$\sum\sum_{j\neq i}(F(\,Cl_i,T)/(|T|)(F(Cl_j,T)/(|T|) \tag{1}$$

Two critical parameters must be defined in constructing an RFC anticipation model: the count of trees (N, user-defined) and the input variables assigned to each tree. Comprising N DTs, RFC jointly utilizes their anticipations to determine the class of new data points through a voting mechanism [42].

2.2 Sea Horse optimizer (SHO)

Zhao et al. [43] introduced the SHO, a novel metaheuristic inspired by swarm intelligence and derived from the unique actions of SHs, including their transience, hunting strategies, and birthing strategies. The SHO is designed to adapt and survive in its environment, drawing inspiration from these key characteristics of SHs.

SHO entails four steps: 1_initialization, 2_mobility, 3_predation, and 4_breeding, with thorough explanations below.

2.2.1 Initialization step

Like various other metaheuristic schemes, SHO initiates by establishing the group. In this instance, the SHs within the group are potential solutions to an issue within the search domain, expressed through Eq. (2):

$$S=\begin{bmatrix} x_1^1 & \ldots & x_1^d \\ \ldots & \ldots & \ldots \\ x_P^1 & \ldots & x_P^d \end{bmatrix} \tag{2}$$

d displays the dimensionality of the variable, P signifies the group volume, and s displays the SHs in the group.

To create member solutions, the upper bound (Ub) and lower bound (Lb) of the problem were deployed as first spots for random creation. The process for creating the $i-th$ member, X_i, in the search domain [Lb, Ub], is outlined by Eqs. (3) and (4).

$$X_i=\left[x_i^1,\ldots,x_i^d\right] \tag{3}$$

$$x_i^j = rand*(Ub^j-Lb^j)+LB^j \tag{4}$$

Ub and Lb for the $\mathrm{j}-\mathrm{th}$ variable in the enhanced issue is displayed as $\mathrm{Ub^j}$ and $\mathrm{Lb^j}$, accordingly.

rand displays a random number within the [0, 1] range, where:

j displays an integer from 1 to d (dimensionality of the problem), d displays the dimensionality of the problem, i displays a positive integer from 1 to P (size of the group), P displays the size of the group, $\mathrm{x_i^j}$ signifies the $\mathrm{j}-\mathrm{th}$ aspect of the $\mathrm{i}-\mathrm{th}$ member in the group.

When addressing a minimum/maximum enhancement issue, the member exhibiting the lowest/highest fitness degree is recognized as $\mathrm{X_b}$, showcasing the best resolution. The value of $\mathrm{X_b}$ can be calculated using Eq. (5):

$$X_b=\arg_{\min or \max}\left(f(X_i)\right) \tag{5}$$

$f(X_i)$ displays the value of the objective function for a particular task.

2.2.2 Transition step

SHs exhibit varied transition schemes influenced by a normal distributed random spread (0,1). Balancing exploration and exploitation, a cut-off point at $r_1=0$ divides SHs into halves for local and global search. Later algorithm steps handle the transition treatment.

First step:

SHs spiral in response to ocean vortices. If the chance value r_1 surpasses the SHO limit, the scheme emphasizes local exploitation. SHs move spirally toward the best resolution X_b, using Lévy flights for the step size. This benefits exploration in early cycles and prevents over-localization. The spiral transition dynamically adjusts the rotation angle, expanding the search domain. Eq. (6) is employed to create a fresh position for SHs.

$$\begin{aligned} X_{new}^1(t+1) &= X_i(t)+Levy\,(\lambda)((X_b(t) \\ &\quad -X_i(t)*x*y*z \\ &\quad +X_b(t)) \end{aligned}$$
$$h.t\begin{Bmatrix} x=p*\cos(\theta) \\ y=p*\sin(\theta) \\ z=p*\theta \\ p=u*e^{\theta v} \end{Bmatrix} \tag{6}$$

The parameters u and v characterize the logarithmic spiral, influencing the stem length (p), with a constant set to 0.05 for every u and v combination. The three-dimensional coordinates under spiral transition are displayed by $x, y,$ and z. θ is chosen haphazardly within the range of $[0, 2\pi]$.

The Lévy flight spreadfunction (Levy(z)) is gauged by Eq. (7).

$$Levy(z) = h * \frac{\omega * \sigma}{|k|^{\frac{1}{\lambda}}} \quad (7)$$

Random positive numbers w and k are chosen from the range of zero to one. The variable h is fixed at 0.01, and λ is haphazardly picked from the interval [0, 2], with a specific value of 1.5. The computation of σ is identified by applying Eq. (8).

$$\sigma = \left(\frac{\Gamma(1+\lambda) * \sin\left(\frac{\pi\lambda}{2}\right)}{\Gamma\left(\frac{1+\lambda}{2}\right) * \lambda * 2^{\left(\frac{\lambda-1}{2}\right)}}\right) \quad (8)$$

Second step:

This step illustrates SHs' Brownian transition, which was influenced by ocean waves. If r_1 is on the left of the restriction, SHO shifts to a drifting mode to avoid local optima. As described by Eq. (9), Brownian transition extends SHs' transition range for enhanced exploration in the search domain.

$$X_{new}^1(t+1) = X_i(t) + rand * l * \beta_t * (X_i(t) - \beta_i * X_{best}) \quad (9)$$

$$h.t\left\{\beta_t = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right)\right\}$$

The random walk coefficient for Brownian transition is displayed by β_i, and a fixed parameter with a value of 0.05 is represented by the symbol l.

The fresh position of the SH at cycle t can be gauged by mixing the two described situations with the use of Eq. (10):

$$X_{new}^1(t+1) = \begin{cases} X_i(t) + Levy(\lambda)\left(\left(X_b(t) - X_i(t)\right) * x * y * z + X_b(t\right. \\ X_i(t) + rand * l * \beta_t * (X_i(t) - \beta_i * X_b), \ r_1 : \end{cases} \quad (10)$$

2.2.3 Predation step

When SHs hunt for zooplankton, success or failure is identified by a random number, r_2, created by SHO. With a probability of over 90% for successful predation, the critical value of r_2 is set at 0.1. Effective hunting, indicated by r_2 greater than 0.1, involves the SH approaching, overtaking, and capturing the prey (ideal resolution). Unsuccessful attempts result in sea horse and prey moving in the opposite direction, indicating continued exploration. The predation behavior is mathematically represented by Eq. (11).

$$X_{new}^2(t+1) = \begin{cases} \alpha * (X_b - rand * X_{new}^1(t) + (1-\alpha) * X_b, & if \ \ r_2 > 0.1 \\ (1-\alpha) * (X_{new}^1(t) - rand * X_b) + \alpha * X_{new}^1(t), & if \ \ r_2 \le 0.1 \end{cases} \quad (11)$$

The refreshed position of the SH after transition at cycle t is displayed by $X_{new}^1(t)$. The variable r_2 is a haphazardly created integer in the interval of 0 to 1.

The computation outlined in Eq. (12) determines that the SH's transition step size diminishes linearly with cycles when chasing prey.

$$\alpha = \left(1 - \frac{t}{T}\right)^{\frac{2t}{T}} \quad (12)$$

T displays the algorithm's maximum number of cycles.

2.2.4 Breeding behavior phase

The group is split into male and female groups based on fitness levels to address male SHs' breeding action. In SHO, members with the highest fitness become selected fathers, while the rest form the group of chosen mothers. Eq. (13) demonstrates that this separation hinders excessive localization of fresh approaches and facilitates the inheritance of beneficial traits by both mothers (M) and fathers (F), ultimately benefiting the next generation.

$$\begin{cases} F = X_{sort}^2(1:\frac{P}{2}) \\ M = X_{sort}^2(\frac{P}{2} + 1:p) \end{cases} \quad (13)$$

X_{sort}^2 signifies the solutions X_{new}^2 sorted by increasing fitness values. In SHO, mothers and fathers match the female and male groups. It functions on the presumption that fresh offspring arise from the chance pairing of females and males. Efficiency is maintained by assuming each sea horse pair produces only one offspring, as illustrated in Eq. (14).

$$X_i^{offspring} = r_3 X_i^F + (1 - r_3) X_i^M \quad (14)$$

The variable i is a positive value in the range $[1, \frac{p}{2}]$, where p is a metric. X_i^F and X_i^M denote the haphazardly selected male and female members, respectively. The integer r_3 is haphazardly created and falls within the range [0, 1]. Fig. 1 displays the diagram of SHO. In this figure, t represents the iteration.

Figure 1: Flowchart of SHO

2.3 Jellyfish search algorithm (JSO)

A recent addition to swarm-based metaheuristics is JSO, developed by Chou and Truong in 2021 [44]. JSO mimics the way jellyfish search for food in the ocean [45].

2.3.1 Numerical framework

JSO adheres to three theoretical standards:

2.3.1.1. Marine flow

Jellyfish can sense the path of marine flows (as per Eq. (15)) to discover and consume smaller planktonic forms.

$$\overrightarrow{OC} = X' - \beta \times M \times d(0,1) \quad (15)$$

Here, $\vec{D}$ displays the direction of the marine flow, β ($\beta > 0$) is the coefficient defining the length distribution of $\overrightarrow{OC}$, X' displays the place of the current best jellyfish in the swarm, and M is the mean location of all jellyfish.

The refreshed position of every jellyfish can be articulated as follows:

$$X_i(t+1) = X_i(t) + d(0,1) \times \overrightarrow{OC} \quad (16)$$

After adjusting each jellyfish's situation, a favorable place, potentially with increased food source availability, is selected as the jellyfish's current position.

2.3.1.2. Jellyfish bloom

Jellyfish within a bloom display two kinds of transitions: passive and active. Here, mathematical schemes for these transitions are presented:

$$\text{Passive transition:} \quad X_i(t+1) = X_i(t) + \lambda \times d(0,1) \times (w_b - L_b) \quad (17)$$

Here, λ (λ > 0) is a coefficient linked to the degree of passive transition. The lower bound, w_b, and the upper bound, L_b, define the search domain.

$$\text{Active transition:} \quad X_i(t+1) = X_i(t) + r(0,1) \times \vec{D}$$

Were

$$\vec{D} = \begin{cases} X_i(t) - X_j(t) & if \quad g(X_i) < g(X_j) \\ X_j(t) - X_i(t) & if \quad g(X_i) \geq g(X_j) \end{cases} \quad (19)$$

The values of the objective function for jellyfish i and j are displayed as $g(X_i)$ and $g(X_j)$ respectively.

2.3.1.3. Time management system

It governs both the transition of the two types of jellyfish in the bloom and their transitions toward marine flows. The function representing this time control is expressed as:

$$T(t) = \left| \left(1 - \frac{t}{MaxIter}\right) \times (2 \times d(0,1) - 1 \right| \quad (20)$$

Here, t displays the time index, expressed as the cycle count, and $MaxIter$ displays the peak count of cycles.

2.3.2 Group initialization

The initial group is created using the Logistic map.

$$X_{i+1} = \upsilon X_i(1 - X_i), \quad 0 \le X_0 \le 1 \tag{21}$$

Here, X_i displays the chaotic value corresponding to the location of the $i-th$ jellyfish and X_0 displays a location created haphazardly. Throughout all experiments, the parameter υ is fixed at a value of 4.

2.3.3 Boundary regulation system

If a jellyfish exceeds the boundaries of the defined search domain, it will be positioned in those boundaries using Eq. (37).

$$\begin{cases} X'_{i,r} = (X_{i,r} - W_{b,r}) + L_{b,r} & if \quad X_{i,r} > W_{b,r} \\ X'_{i,r} = (X_{i,r} - L_{b,r}) + W_{b,r} & if \quad X_{i,r} < W_{b,r} \end{cases} \tag{22}$$

Here, $X_{i,r}$ and $X'_{i,r}$ display the present and refreshed place of the d-th dimension for the i-th jellyfish. $W_{b,r} and\ L_{b,r}$ denote the lower and upper bounds, respectively, for the $r-th$ dimension in the search domain.

The diagram for JSO is illustrated in Fig. 2, and the corresponding pseudocode is provided below.

Initialization phase
Define the parameters for the algorithm: number of population (n_{pop}) and maximum cycle ($MaxIter$) generate the primary group $X_i(i = 1,2, \dots, n_{pop})$ using Eq. (21)
Assess the initial group, $f(X_i)(i = 1,2, \dots, n_{pop})$
Identify the current top-performing jellyfish (X')
Initialize time: $t = 1$
Cyclic body of the algorithm
While $t \le MaxIter$
For $i = 1$: n_{pop}
Gauge the time regulation $T(t)$ using Eq. (20)
If $T(t) \ge 0.5$
Calculate the path of the marine flow using Eq. (15)
Compute the refreshed position of the $i-th$ jellyfish using Eq. (16)
Else
If $(1 - T(t)) < rand(0,1)$
Calculate the refreshed position of the $i-th$ jellyfish using Eq. (17)
Else
Compute the refreshed position of the $i-th$ jellyfish using Formulas (18) and (19)
End if
End if
Verify restriction situations using Eq. (22)
Examine the fresh place of the i-th jellyfish
Refresh the place of the i-th jellyfish (X_i)
Update the place of the currently best jellyfish (X')
End for i
$t = t + 1$
End while
Output the ideal outcomes

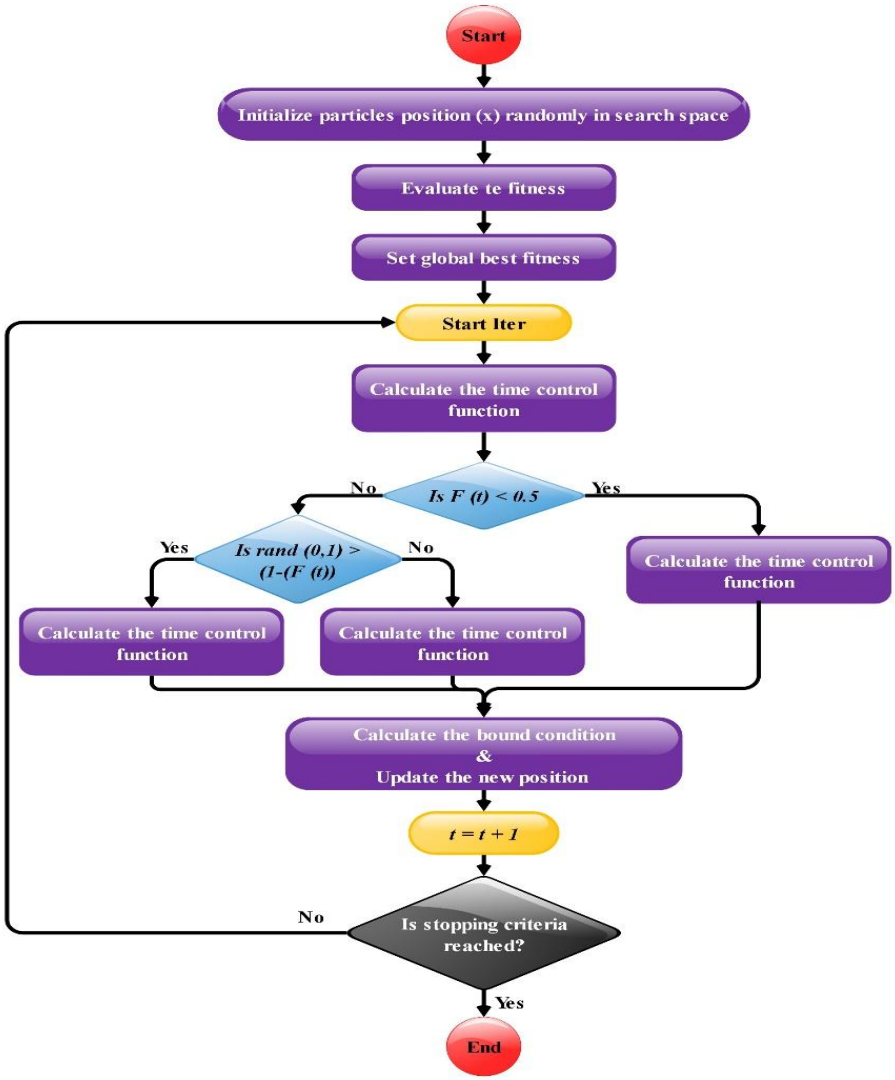

Figure 2: Flowchart of JSO

2.4 Data collection

An integral phase in the data mining procedure entails thoroughly preprocessing the database. During this step, textual information is meticulously transformed into numerical values, laying the basis for utilizing machine learning schemes and sophisticated statistical approaches. This is a critical transformation that will enable an in-depth analysis of the database and, therefore, yield material insight into its usage.

The database contains different factors organized carefully to distinguish between phishing websites and real ones. The data is presented in a structured framework that allows for in-depth, organized scrutiny for more accurate and reliable analysis in the future.

The present work examines a manifold of inputs over various dimensions that drastically affect the decision between phishing and legitimate websites. Its comprehensiveness embraces a wide range of elements, from technical indications to behaviorist trends, to delve deeply into the interactions related to web security. The dataset gathered from the published study [46].

- *SFH (Server Form Handler)*: Evaluates the security of form submissions on a webpage.
- *Pop-Up Window*: Assesses the presence or behavior of pop-up windows on a webpage.
- *SSL final state*: displays the final state of an SSL (Secure Sockets Layer) connection, providing insights into the website's security.
- *Request URL*: This examines the URLs requested during a web page's loading. It is often used to assess potential security threats.
- *URL of Anchor*: Analyzes the anchor (hyperlink) tags in the webpage, assessing the quality and security of linked URLs.
- *Web traffic*: Measures a website's web traffic or popularity, which can indicate its trustworthiness.
- *URL Length*: Assesses the length of the URL, as excessively long URLs may be associated with phishing or deceptive websites.
- *Age of domain*: Displays the age of the domain, with older domains often considered more trustworthy.

- *Having IP Address*: Showcases whether the URL has an IP address, and the presence of an IP address in the URL may be a security concern.

A diversified strategy like this would ensure completeness in the analysis regarding various factors that, when combined, help differentiate phishing websites from real ones. In this respect, it involves a broad appraisal of technical criteria, behavioral trends, and contextual influences. This is multi-dimensional research in this direction, aspiring to encapsulate the intricacy of detecting deceitful online actions versus real sites.

Fig. 3 presents the correlation matrix, illustrating the relationships between the input features and the target classification outcome (i.e., whether a URL is phishing, suspicious, or legitimate). The figure uses color intensity to represent the strength of the correlation, with darker shades indicating stronger relationships. The most influential feature in this analysis is "Having an IP Address," which shows the highest positive correlation score of 3.8, highlighting its critical role in distinguishing fraudulent websites. This aligns with cybersecurity principles, as phishing sites often use direct IP addresses to bypass domain reputation checks. Additionally, the SSL final state exhibits a moderately strong correlation of 1.9, indicating that the presence or absence of a secure SSL certificate substantially affects phishing likelihood. Another significant input is the domain age, which shows a positive correlation, emphasizing that newer domains are often associated with phishing behavior. Conversely, SFH presents a negative correlation of -0.70, suggesting that poorly configured or insecure form handlers are strongly associated with fraudulent websites. Overall, the correlation analysis underscores that most features negatively influence a website's authenticity, with only a few—like Web Traffic (0.21) and Having an IP Address (1.7)—exerting clear positive impacts.

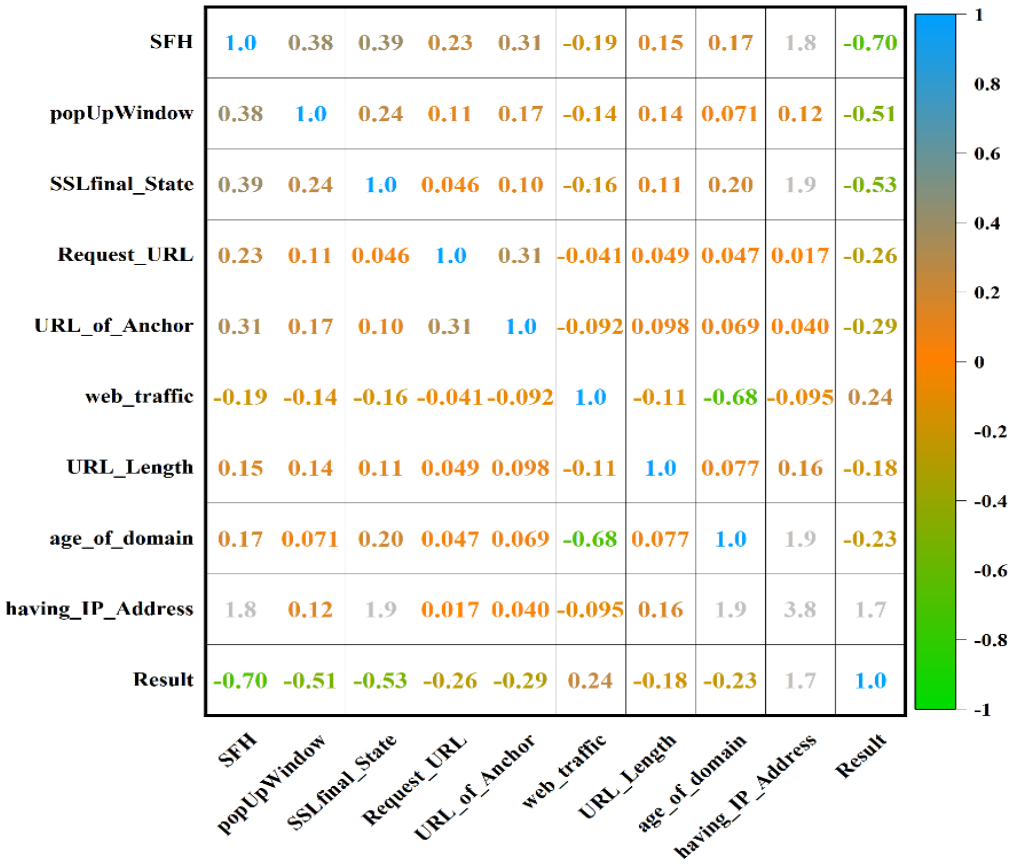

Figure 3: Correlation matrix for the link between inputs and output.

3 Outcomes

3.1 Framework practicality appraisal

Accuracy is a common metric for assessing a framework's total productivity in classifying issues. It relies on True Positives (T_P), True Negatives (T_N), False Positives (F_P), and False Negatives (F_N). However, Accuracy may be less effective in imbalanced data, favoring the majority class. To address this, Recall, Precision, and F1-Score are additional metrics offering nuanced insights into model performance, particularly in imbalanced situations. These metrics, expressed in numerical formulas (typically numbered 23 to 26), collectively refine the appraisal of a categorization model's effectiveness. In addition, Table 2 displays the formula of appraisal metrics.

Table 2: Formulation of appraisal metrics

Metrics	Number
$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}$	(23)
$Precision = \frac{T_P}{T_P + F_P}$	(24)
$Recall = T_P R = \frac{T_P}{P} = \frac{T_P}{T_P + F_N}$	(25)
$F1_score = \frac{2 \times Recall \times Precision}{Recall + Precision}$	(26)

3.2 Convergence outcomes

Convergence diagrams are widely used in scholarly communication to visually illustrate the optimization progress in schemes or schemes across cycles. Fig. 4 illustrates the convergence behavior of the two optimization-based models—RFSH and RFJS—over 200 learning cycles. Initially, both models start from similar baselines. The RFJS model demonstrates an early surge in performance during the first few cycles, indicating a faster initial convergence. However, this gain plateaus over time. In contrast, the RFSH model shows a more consistent and gradual improvement in accuracy throughout the training process. By the 200th cycle, RFSH achieves a superior final accuracy of approximately 0.91, compared to 0.89 for RFJS. This convergence pattern highlights the resilience and adaptive efficiency of the RFSH model, particularly in later training stages. The performance advantage of RFSH may be attributed to the exploitation–exploration balance managed by the Sea Horse Optimizer, enabling more refined learning during prolonged iterations. Both models were fine-tuned using a random search hyperparameter optimization technique, which explored multiple combinations of parameters to maximize model performance.

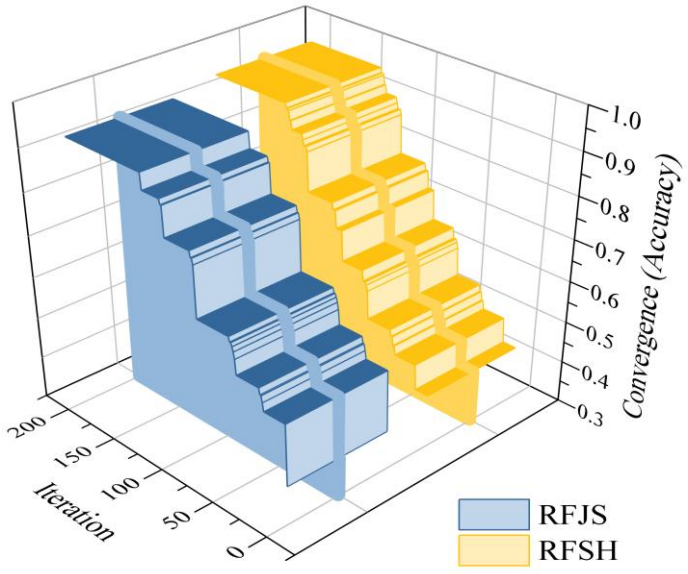

Figure 4: 3D ribbons for the convergence of hybrid models

3.3 Comparing outcomes of predictive schemes

Table 3 presents a thorough overview of the outcomes derived from the developed RFC schemes, providing a detailed insight into their performances. In addition, Fig. 5 employs a 3D bar chart to visually illustrate how assessors evaluated these schemes, aiming to pinpoint the model that excels in precision when predicting practical results. A considerable portion of the database endures intensive training, while the remaining values undergo meticulous testing. The outcomes, covering the entire database, are carefully noted in Fig. 5, graphically showcasing the essential parameter for scheme appraisal. Accuracy appraisal is performed in three phases: Train, Test, and All. The outcomes observed during the training phase across all three schemes expose superior performance relative to the subsequent phases. A comparative analysis of the data from both the training and test phases, as presented in the consolidated All phase, highlighted that the RFSH model, exhibiting an approximate value of 0.952, surpasses the optimized RFJS model with a value of 0.932 and the single RFC model, which records a value of 0.91. This highlights the RFSH model's distinction as superior in this evaluative context. The elucidated values from Table 3 are graphically depicted in Fig. 5. Notably, the RFC and RFJS schemes exhibit relatively consistent columnar patterns. However,

the RFHS model displays a decrement in performance during the test section, followed by a subsequent recovery in the all-encompassing section. This resurgence underscores its superiority and establishes a notable advantage over the other schemes.

Table 3: Result of RFC-based developed models in the training, testing, and All sections.

Phase	Index values	Schemes		
		RFC	RFJS	RFSH
Train	Accuracy	0.9113	0.9324	0.9567
	Precision	0.9104	0.9324	0.9570
	Recall	0.9113	0.9324	0.9567
	F1 _score	0.9102	0.9324	0.9567
Test	Accuracy	0.9089	0.9310	0.9409
	Precision	0.9095	0.9323	0.9423
	Recall	0.9089	0.9310	0.9409
	F1 _score	0.9083	0.9312	0.9409
All	Accuracy	0.9106	0.9320	0.9520
	Precision	0.9097	0.9320	0.9524
	Recall	0.9106	0.9320	0.9520
	F1 _score	0.9095	0.9320	0.9520

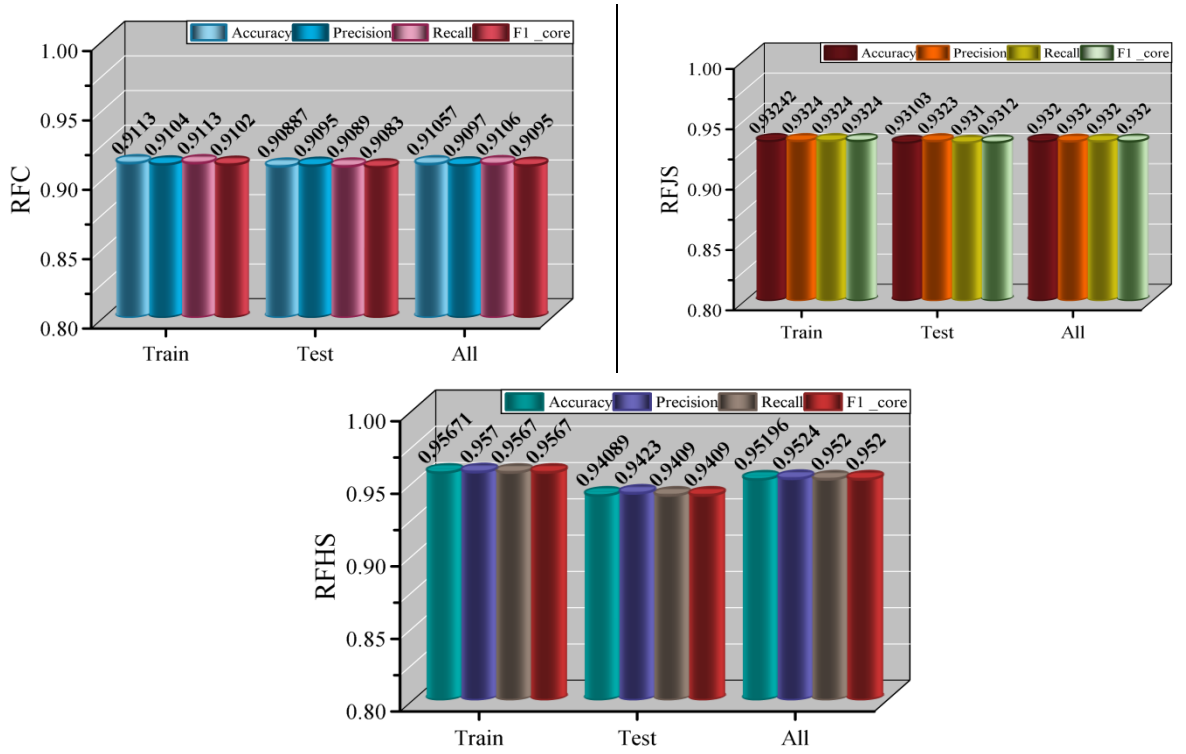

Figure 5: Achievement-based 3D bar chart for the developed models' productivity by evaluators

3.4 Categorization outcomes

Table 4 and Fig. 6. facilitate a comparison of the model's accuracy in predicting legitimate, phishing, and suspicious instances. Examining Fig. 6. indicates specific gauged values, where phishing instances are recorded as 548, suspicious instances as 702, and legitimate instances as 103. Notably, the RFSH model exhibits the highest correct anticipation rates across the three categories, with numerical values corresponding to 101 legitimate cases, 514 instances of phishing, and 673 instances of suspicious categories. Additionally, Table 4 underscores the precision values, revealing a remarkable match of 95.72% for phishing, 95.73% for suspicious, and 89.38% for legitimate instances within the RFSH model. This

underscores its pronounced superiority in accuracy. Further substantiating this superiority, the F1-score and Recall sections also reflect favorable outcomes for the RFSH model.

Table 4: Appraisal indexes of the designed schemes' productivity drawing on grades.

Model	Grade	Index values		
		Precision	Recall	F1-score
RFC	Phishy	0.918	0.9051	0.9084
	Suspicious	0.917	0.9444	0.9305
	legitimate	0.8488	0.7087	0.7725
RFJS	Phishy	0.9336	0.9234	0.9284
	Suspicious	0.9392	0.9459	0.9425
	legitimate	0.875	0.8835	0.8792
RFSH	Phishy	0.9572	0.938	0.9475
	Suspicious	0.9573	0.9587	0.958
	legitimate	0.8938	0.9806	0.9352

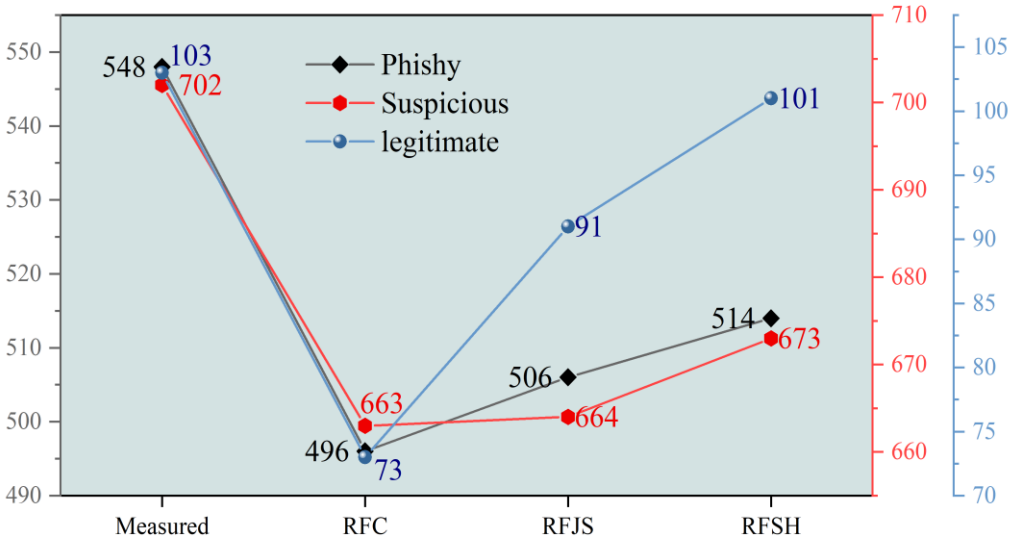

Figure 6: Line-symbol plot for comparing the measured and predicted values

Utilizing the confusion matrix enables the determination of miscategorizations for each model out of 1353 websites in Fig. 7. A detailed examination of the columns illustrates specific miscategorization numbers for each model. The RFC model exhibits 52 miscategorizations in phishy, 39 miscategorizations in suspicious, and 30 miscategorizations in legitimate instances. Similarly, the RFJS model records 42 miscategorizations in phishy, 38 miscategorizations in suspicious, and 12 miscategorizations in legitimate cases. On the other hand, the RFSH model manifests 34 miscategorizations in phishy, 29 miscategorizations in suspicious, and two miscategorizations in legitimate cases.

Given the fewest anticipation errors compared to the gauged values, RFSH rises as the most favorable scheme for future anticipations. This miscategorization reduction underscores its potential for enhanced accuracy and reliability in subsequent predictive scenarios.

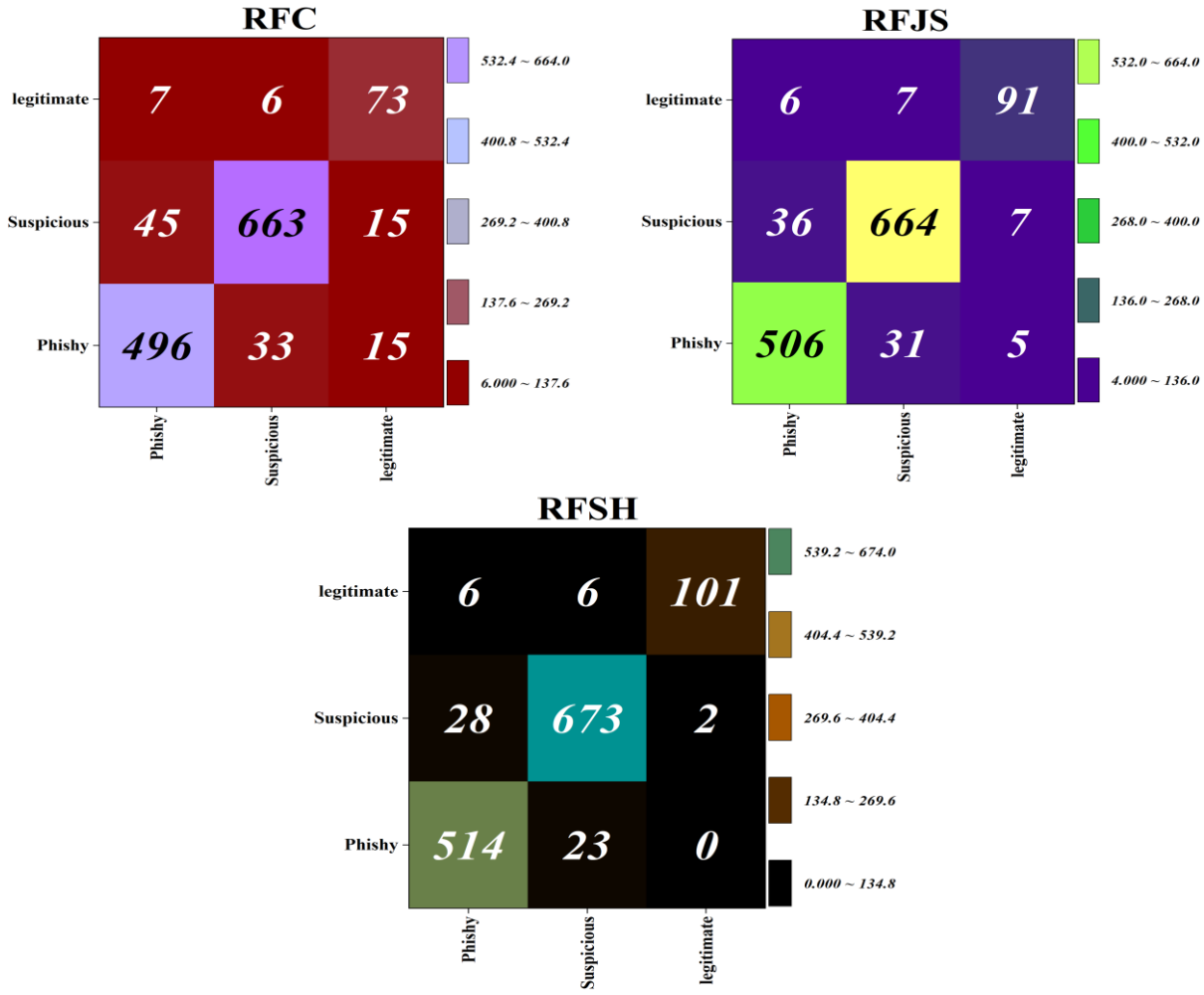

Figure 7: Confusion pattern showcasing the accuracy of each model

Fig. 8 presents the Receiver Operating Characteristic (ROC) curves for three models—RFC, RFJS, and RFSH—to evaluate their capability in distinguishing phishing, suspicious, and legitimate websites. The ROC curve illustrates the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) across different classification thresholds, where a curve closer to the top-left corner signifies superior classification performance. The baseline RFC model performs adequately with an Area Under the Curve (AUC) of 0.8993 but shows a comparatively higher FPR. Upon integrating optimization strategies, the RFJS model achieves a notable improvement with an AUC of 0.9385, reflecting enhanced sensitivity and reduced misclassifications. The RFSH model, with the highest AUC of 0.9654, demonstrates exceptional discriminative ability, with a steep curve that indicates high sensitivity and minimal false positives. This figure underscores the effectiveness of incorporating metaheuristic optimization algorithms into the Random Forest framework, resulting in significant performance gains, with the RFSH model emerging as the most robust and reliable for phishing detection.

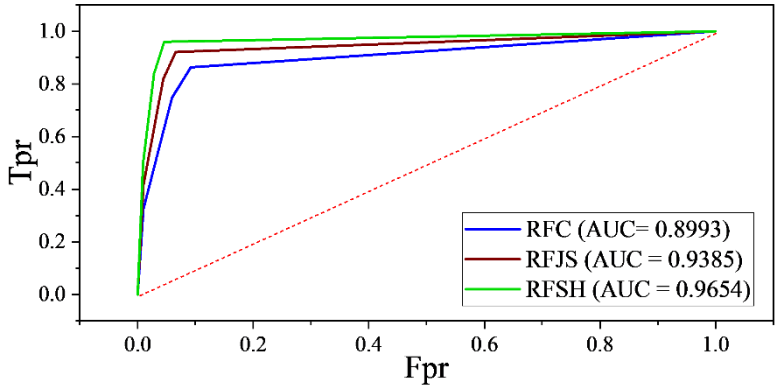

Figure 8: Receiver Operating Characteristic (ROC) curve for the top-performing hybrid model

The SHAP analysis results in Fig. 9 highlight the most influential features in categorizing websites as phishy, suspicious, or legitimate. Among all features, the SFH demonstrates the highest importance, particularly for identifying phishy and legitimate websites, indicating that insecure form handling is a strong indicator of phishing behavior. Pop-Up Windows and SSL Final State are impactful features, showing that deceptive pop-ups and lack of proper SSL implementation are common traits in phishing websites, while secure SSL practices are associated with legitimate sites. Request URL and URL of Anchor have moderate importance, emphasizing the role of embedded links in signaling potential malicious intent. Web traffic, URL length, and age of the domain offer additional discriminative power, especially in differentiating legitimate sites from suspicious or phishy ones. Notably, the feature of Having an IP Address has minimal influence across all categories, suggesting that its standalone effect is limited in modern phishing detection. Overall, this analysis affirms that the model relies on behaviorally relevant features and offers a transparent interpretation of how each input contributes to the classification outcome.

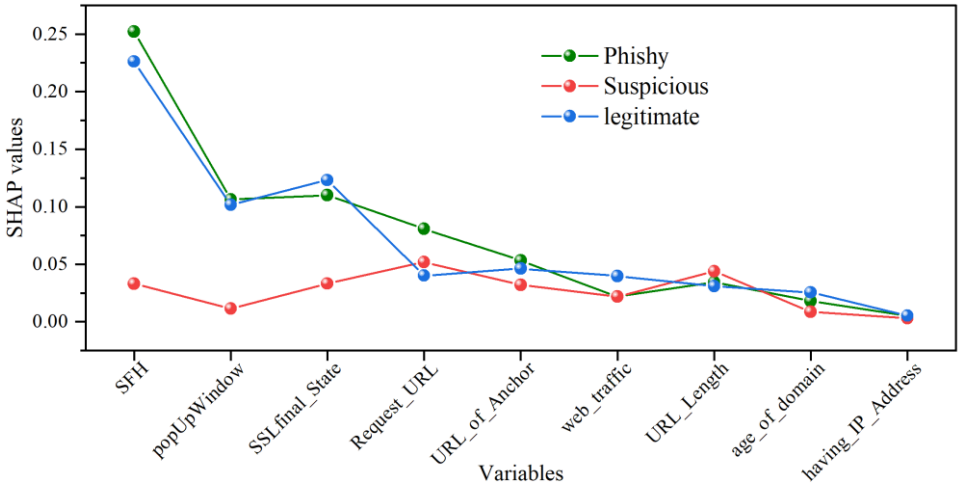

Figure9: Impact of the input variables on models' output based on SHAP sensitivity analyses.

To assess the statistical significance of the differences in the performance of the three models, including RFC, RFSH, and RFJS, a one-way Analysis of Variance (ANOVA) test was conducted. The results are presented in Table 5. The F-values for RFC (0.2523), RFSH (0.0587), and RFJS (0.0491) are all notably low, and their corresponding P-values are substantially greater than the conventional significance level of 0.05 (specifically, 0.6155, 0.8086, and 0.8246, respectively). These high P-values indicate no statistically significant difference in the mean performances of the models based on the dataset under consideration. Despite RFSH achieving a higher accuracy in practice, the ANOVA results suggest that the observed performance improvements over RFC and RFJS may not be statistically significant at the 95% confidence level. This could be attributed to the relatively small test set size or the inherent variability in model predictions across different folds.

Table 5: Result of statistical analyses based on ANOVA

Model	F-value	P-value
RFC	0.2523	0.6155
RFSH	0.0587	0.8086
RFJS	0.0491	0.8246

4 Discussion

The results of this study indicate that both optimized models, including RFSH and RFJS, outperform the baseline RFC in phishing website classification. The RFSH model achieved the best performance with an accuracy of 95.20%, followed by RFJS (93.20%) and RFC (91.06%). These gains are attributed to the capability of the metaheuristic optimizers to fine-tune model parameters, improving convergence, reducing overfitting, and enhancing generalization.

The superior performance of RFSH compared to RFJS may stem from the SHO's more effective balance between exploration and exploitation. The SHO mimics the spatially aware swimming patterns of sea-horses, which may help it escape local optima better than the JSOA, whose dynamics are influenced by time-varying ocean currents and may be more susceptible to premature convergence.

Table 6 presents a comparative analysis of the approach against state-of-the-art phishing detection models from recent studies. While the Extra Trees Classifier by Awasthi and Goel [46] reports a marginally higher accuracy (98.59%), other ensembles and gradient-boosted models demonstrate performance comparable to or lower than the proposed RFSH model. For instance, Gradient Boosting (GB) in Pandey et al. [47] yielded 95.7%, only slightly higher than our result, whereas XGBoost and GBDT methods in Yang et al. [48] achieved 88.46% and 89.04%, respectively.

Table 6: Comparison of the current work with state of art phishing prediction articles.

Source Article	Model	Result (%)
Awasthi and Goel [47]	Voting ensemble	95.51
	Extra trees classifier	98.59
Yang et al. [48]	GBDT	89.04
	XGB	88.46
Pandey et al [49]	GB	95.7
	DT	94.2
Current Study	RFSH	95.20

The RFSH model offers competitive performance compared to these works, especially considering its relatively low computational complexity and interpretability. Models like Extra Trees may require more extensive feature engineering and hyperparameter tuning, whereas the proposed RFSH balances efficiency and accuracy. Despite these promising results, there are several limitations to consider. First, the dataset was compiled from existing literature and may not fully capture the variability of real-time or zero-day phishing websites. Second, the static feature set may not be adaptable to evolving phishing techniques. Third, the study does not evaluate model latency or deployment feasibility in real-world scenarios. Future work will incorporate real-time URL streams, adaptive feature extraction, and ensemble optimization strategies to improve robustness and scalability further. Additionally, exploring hybrid deep learning approaches and evaluating model performance on live threat feeds could offer deeper insight into practical deployment in cybersecurity systems.

4.1 Real-world application

The proposed RFSH and RFJS models hold strong potential for real-world cybersecurity applications, particularly for detecting phishing websites in real-time. These models can be integrated into security tools such as browser extensions, secure web gateways, email filtering systems, and SIEM/SOAR platforms. Their main advantage lies in their ability to analyze website features and accurately flag suspicious activity quickly. From a computational standpoint, while training the models—especially with optimization algorithms like SHO and JSO—requires moderate to high computational resources, the inference phase (actual prediction) is lightweight and fast. This makes the models suitable for real-time deployment, even on devices with limited resources. Moreover, their compatibility with various programming languages and deployment frameworks allows for easy integration into current infrastructures. They can be deployed via APIs or containerized environments (e.g., Docker) and scaled across cloud-based or enterprise systems. The models are also maintainable, as they support periodic retraining to adapt to new phishing techniques and can be updated remotely. In summary, RFSH and RFJS offer a practical, scalable, and efficient solution for phishing detection in real-time security systems, with minimal latency, strong interoperability, and manageable computational demands.

4.2 Model adaptability and resilience against evolving phishing techniques

Phishing techniques are constantly evolving, making it crucial for detection models to remain adaptive and resilient. While demonstrating strong performance on the current dataset, the proposed model may face challenges when exposed to newly developed phishing tactics that differ significantly from the patterns it has learned. To address this, the model would benefit from periodic retraining using updated datasets that reflect emerging threats and evolving attack vectors. Incorporating a continuous learning framework or active learning mechanism could enhance adaptability, allowing the model to identify novel patterns in real-time and adjust accordingly. Additionally, integrating threat intelligence feeds and community-reported phishing samples could ensure the model remains current and effective against the latest phishing strategies. Acknowledging and preparing for the dynamic nature of phishing threats significantly increases the proposed detection system's practical utility and long-term relevance.

5 Conclusion

This research classifies 1353 websites using machine learning (RFC model) and optimized schemes (Sea Horse and Jellyfish). It enhances technology for privacy and security, preventing information theft. The database is divided into subsets, and accuracy is assessed using metrics. Ultimately, the findings of this research are summarized as follows, which contribute to significant advancement in technology:

- The presence of an IP address exhibited the most positive impact on the outcome, while the Server Form Handler had the most negative effect. This highlights a substantial discrepancy in the significance of these inputs, emphasizing the critical role of the IP address and the adverse consequences linked to the Server Form Handler.
- The data table analysis indicates that the RFSH consistently outperformed the other two schemes in the training, test, and integration phases. The RFSH model showed a significant superiority of 2.14% over the RFJS model and a notable 4.54% advantage over

the RFC model in overall accuracy appraisal. Notably, the RFSH model accurately predicted a substantial number (1353) of sites with an impressive 95.19% correct anticipation rate, reinforcing its effectiveness in predictive modeling compared to alternative schemes.

- The tabular outcomes were visually represented in figures, enhancing visibility and comprehension. Additional figures delineated the miscategorization rates, revealing 1.41 times more miscategorizations for the RFJS model and 1.86 times more for the RFC model than the RFSH model. Furthermore, the ROC diagram for the superior RFSH model illustrated a Micro Average ROC curve with a significantly larger area, which is evidenced by this.
- Substantiates its role as the primary agent or actor in the superiority of this model.

Authorship contribution statement

Yuan Ma: Writing-Original draft preparation Conceptualization, Supervision, Project administration.
Juan Zhao: Methodology, Software
Yongqiang Zhang: Validation.

Data availability

The scholars will make the raw data supporting this article's conclusions available without undue reservation.

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 displays honest work.

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Ethical approval

All scholars have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

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TSTL: A Hybrid TextRank-LP and TDNN-LSTM Model for Public Opinion Monitoring in Emergency Events

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Online public sentiment during emergencies often hinders effective crisis management. Timely and accurate identification and prediction of this sentiment are vital, yet existing approaches face challenges related to high identification delays and low accuracy. To address these issues, this study proposes a model for the evolution of network public opinion based on the TextRank-Label Propagation Algorithm (TextRank-LP). The model fully utilizes the information extraction capability of TextRank-LP, while integrating the strengths of Time Delay Neural Networks and Long Short-Term Memory networks in handling time-series data. In the validation of the keyword extraction algorithm, the Natural Language Processing and Chinese Computing dataset was used, which contains tens of thousands of text samples. The results showed that the accuracy of the proposed algorithm reached 95.1%, higher than the 92.1% of Term Frequency Across Document Frequency, 88.1% of Support Vector Machine, and 86.0% of Bidirectional Long Short Term Memory network (Bi-LSTM). The F1 value of the proposed algorithm reached 94.6%. In practical testing using the 2019 NBA China controversy dataset, the model achieved a 100% accuracy rate in identifying declining online public opinion and an average recognition accuracy rate of 92.5% for each stage. Meanwhile, the model's prediction time for online public opinion 12 months ahead is 21 minutes, far lower than Bi-LSTM's 47 minutes. These findings indicate that the proposed model demonstrates strong recognition and predictive capabilities for public sentiment in emergencies and provides a novel approach to studying the evolution of online sentiment in such events. This method offers valuable potential for advancing more accurate and efficient research in the field of public sentiment dynamics.

Povzetek: Prispevek predstavi model TSTL, ki združuje TextRank-LP, spektralno gručenje in TDNN-LSTM za spremljanje spletnega mnenja v krizah.

1 Introduction

Online public opinion during sudden events contains substantial false and exaggerated information, which can easily trigger negative emotions among the masses and even lead to the occurrence of extreme events in severe cases [1]. As deep learning and artificial intelligence continue to advance, their techniques, including natural language processing and knowledge graphing, have increasingly been utilized for monitoring online public opinion during emergencies. However, these methods still have certain flaws and require more accurate and efficient approaches to be applied in this domain [2-3]. The TextRank-Label Propagation Algorithm (TextRank-LP) is widely used in text summarization due to its real-time processing capabilities and low operational costs [4]. Additionally, the integration of neural networks can adapt to different types of data by combining the strengths of various neural networks [5]. The existing network public opinion monitoring technology often suffers from weight bias when processing large-scale network texts due to the complexity and diversity of text sources, as well as limitations in processing time series information, making it difficult to accurately predict the development trend of public opinion. Therefore, we propose a method for extracting keywords from online public opinion during. In addition, a monitoring model is introduced to track online public opinion in such situations, which integrates Time Delay Neural Networks (TDNN) and Long Short-Term Memory (LSTM) networks. The research hypothesis is that integrating Spectral Clustering (SC) can further improve keyword extraction performance compared to standard TextRank, and the time series information processing performance of TDNN-LSTM is better than that of standard LSTM or Bidirectional Long Short Term Memory network (Bi-LSTM). The model is expected to be applied in emergency public opinion monitoring and effectively prevent large-scale public opinion crises.

The innovation of this manuscript lies in: (1)

combining TextRank-LP algorithm and SC algorithm, optimizing the keyword extraction process by comprehensively considering the frequency, position, and part of speech information of words. (2) A multi-to-one TDNN-LSTM network architecture has been proposed, which is suitable for monitoring and predicting network public opinion in emergency situations. (3) Integrating the optimized TextRank-LP keyword extraction method and TDNN-LSTM network, achieving full process monitoring from text preprocessing to public opinion prediction.

2 Related works

TextRank has been widely used in various fields of research by scholars both domestically and internationally due to its advantages, such as no need for pre-training and strong adaptability to sentence structures. Sihombing's team developed a summarization system for Indonesian language articles based on TextRank. In experiments with 100 Indonesian articles, the system achieved an accuracy rate of 80% at compression rates of 50%, 40%, and 30% [6]. Gusra et al. developed an automated news summarization method based on TextRank's ability to identify key information, aiming to generate more concise news articles from a large number of online news sources. In tests, this method successfully condensed a sentence with 387 words down to 75 words [7]. To address the performance degradation of speakers in noisy environments, Benhafid et al. optimized TDNN using a time-limited self-attention mechanism and proposed a new hierarchical TDNN speaker model. In testing experiments, the method achieved an accuracy rate 6.85% higher than the comparison method [8]. Qiao's team applied TDNN to the auxiliary detection of heart sound signals. Their method fused hidden feature layers of heart sound signals within a certain time period using an improved TDNN and improved recognition accuracy by masking irrelevant heart sound frequencies. The experimental results showed that the method outperformed existing abnormal heart sound detection methods [9]. Mohbey et al. applied LSTM in public health research. To determine public perceptions of monkeypox, the research used an LSTM-based model to process a tweet dataset about monkeypox. The processing results achieved an accuracy rate of 91% [10]. To solve the problem of low accuracy in traditional deep learning-based waste classification models, Lilhore et al. proposed a sustainable intelligent waste classification method based on LSTM, improving the accuracy of the waste classification model to 95.45% [11].

The study of the evolution of online public opinion has also developed several mature methods and theories, which have been applied in practical monitoring. For example, Yuan's team explored the process of polarization in international attitudes by integrating the information diffusion process and the development of polarization behavior in a network public opinion monitoring model. The team hoped to find the main factors affecting public opinion by adjusting model parameters [12]. Ding et al. researched the factors influencing social media users' opinion identification behavior based on the Theory of Planned Behavior and Deterrence Theory. The findings showed that the severity and authenticity of online public opinion negatively moderate users' subjective norms and attitudes, thereby accelerating the spread of public opinion [13]. Zhang et al. studied the public opinion diffusion pattern during major epidemics by selecting three quantitative indicators: emotional enhancement, differences, and conversion rates. Based on this, they constructed the SIPINRS public opinion diffusion model. The model analysis revealed that the number of initial opinion spreaders significantly affects the development trend of public opinion [14]. Wang et al. proposed a keyword extraction method for online public opinion based on unsupervised spatiotemporal graphs. This method forms clustering topics through keyword similarity and understands the evolution of online public opinion by analyzing the relationship changes between topics. This method has been effectively tested on five datasets [15]. The related work summary table is shown in Table 1.

Table 1: Summary table of related work

Literature	Method	Data set	Result	Limitation
[6]	TextRank	Indonesian language online news collection	Compress 387-word sentences to 75 words (compression rate 80.6%) while retaining core information	Not considering semantic coherence, relying on title quality
[7]	TextRank + TF-IDF	100 Indonesian scientific articles	Accuracy reaches 80% at different compression rates	Insufficient elimination of long text redundancy
[8]	Time limited self attention + graded TDNN	VoxCeleb1/2	Speaker verification accuracy increased by 6.85%	High computational complexity and weak adaptability to dynamic environments
[9]	Improved TDNN + Dynamic Mask Encoder	PhysioNet Heart Sound Database	Abnormal heart sound detection with F1 value of 92.7%	Sensitive to mixed noise
[10]	CNN-LSTM	Monkeypox related tweet	The accuracy of emotion classification	Unprocessed satirical text

		dataset	is 91%	
[11]	CNN-LSTM + Transfer Learning	TrashNet image dataset	The classification accuracy is 95.45%	Real scene lighting changes affect accuracy
[12]	SIR model + dynamic network structure	Public opinion data on the controversy between China and the United States	The predicted F1 value for polarization trend is 88.3%	Not considering cross platform dissemination differences
[13]	Structural equation model	Emergency event social media data	The fitting index reaches 0.93	The relationship between unquantifiable behavior and actual dissemination
[14]	SIPINRS	Major Epidemic Public Opinion Dataset	The initial number of disseminators has a transmission range R^2 of 0.76	Emotional indicators rely on dictionary annotation
[15]	Unsupervised spatiotemporal graph attention	Public Event Dataset	Topic evolution correlation 0.89	Insufficient real-time performance

In summary, although there have been some achievements in the study of the evolution of online public opinion, current research methods still require pre-training on specific texts and have low accuracy in keyword extraction. TextRank-LP, however, can effectively extract keywords from texts without the need for pre-training. Therefore, this study constructs a model for keyword extraction and the study of the evolution of public opinion in emergencies based on TextRank-LP and the integration of TDNN and LSTM. The aim is to extract keywords from online public opinion quickly and accurately, grasp the development patterns of public opinion.

3 Online public opinion monitoring model integrating Textrank-LP and neural networks

3.1 Design of keyword extraction method for online public opinion based on optimized TextRank-LP

TextRank-LP is a text summarization algorithm based on PageRank and label propagation algorithms. It treats sentences as individual points or vectors and determines text similarity based on point similarity [16-17]. The online public opinion of sudden events is highly dynamic and unpredictable, and traditional supervised learning-based keyword extraction methods often require a large amount of labeled data for training, which consumes a lot of time. TextRank-LP, based on graph structure, can utilize the intrinsic information of text to calculate the importance of keywords, avoiding dependence on a large amount of annotated data and enabling quick response and processing of new public opinion data. Therefore, this study designs a keyword extraction method for emergency online public opinion based on TextRank-LP's text summarization ability, with the specific process of keyword extraction shown in Figure 1.

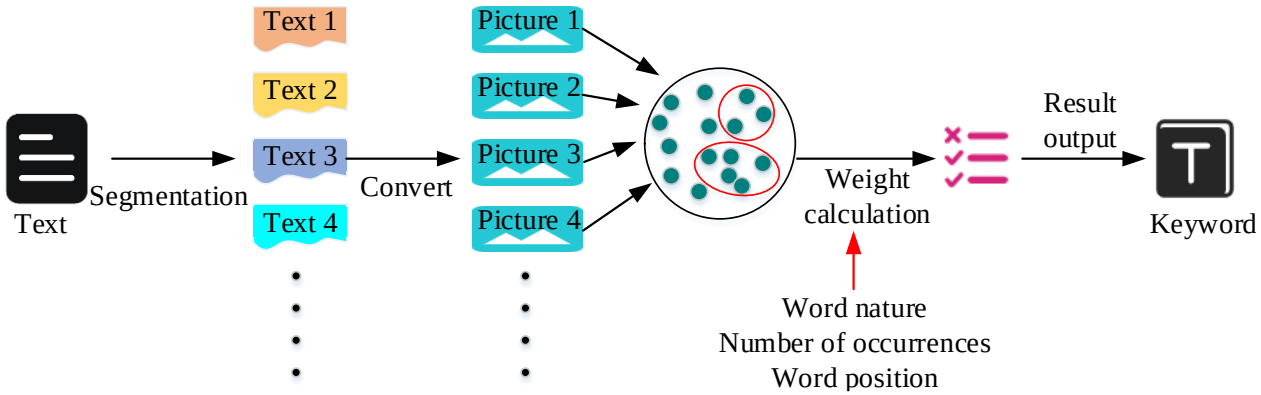


Figure 1: Textrank-LP keyword extraction process diagram

As shown in Figure 1, when extracting keywords, TextRank-LP transforms the text into an undirected graph, where each word is treated as a node in the graph. A node's weight is defined by the quantity of adjacent nodes

and the edges surrounding it. Based on this weight, it is determined whether a word is a keyword. The calculation process is shown in Equation (1).

$$S(v_i) = (1-d) + \sum_{j \in In(v_i)} \frac{w_{ji}}{\sum_{v_k \in Out(v_j)} w_{jk}} S(v_j) \quad (1)$$

In Equation (1), $S(v_i)$ represents the weight value of point v_i, d is the damping factor, $In(v_i)$ is the set of all points pointing to point v_i, $Out(v_i)$ is the set of all points pointed to by point v_i, w is the weight of the edge connecting two nodes, and $S(v_j)$ is the weight value of point v_j. Then, a comprehensive weighting process considering word frequency, position, and part of speech is conducted. The calculation process is shown in Equation (2).

$$W(v_i) = W_1(v_i) * T - OT + W_2(v_i) * Lo + W_3(v_i) * Po \quad (2)$$

In Equation (2), $W(v_i)$ is the comprehensive weight. W_1, W_2, and W_3 represent the weights for word frequency, position, and part of speech, respectively. T and OT refer to the occurrence counts of a word and other words, while Lo and Po represent the position and part of speech attributes of the word. The position of words in a sentence often reflects their importance. Usually, words located at the beginning and end of a sentence are easier to express the core idea. Therefore, the sentence is divided into three regions: the beginning (S), middle (M), and end (E). The weights of each region are w_S, w_M, and w_E, adjusted according to actual needs to ensure that the sum of the weights of the three regions is 1. The importance of different parts of speech varies in text, and by analyzing a large amount of text, the weight of different parts of speech can be determined. For each word, assign corresponding weights based on its part of speech, such as nouns, verbs, adjectives, etc. The final weight value of TextRank-LP is calculated using Equation (3).

$$S(v_i) = (1-d) * W(v_i) + d * W(v_i) * \sum_{v_i \in In(v_j)} \frac{W_{ji}}{\sum_{v_k \in Out(v_j)} W_{jk}} S(v_j) \quad (3)$$

In Equation (3), w is replaced by the comprehensive weight W, which takes more information into account. The SC algorithm captures complex information relationships and groups similar information based on different features [18]. Using the SC algorithm for text classification can effectively improve the keyword extraction speed by keeping similar information within a smaller spatiotemporal range. Moreover, the Laplacian matrix in SC has global optimization properties during feature decomposition, reducing weight propagation bias during keyword extraction and improving accuracy. The SC algorithm process is shown in Figure 2.

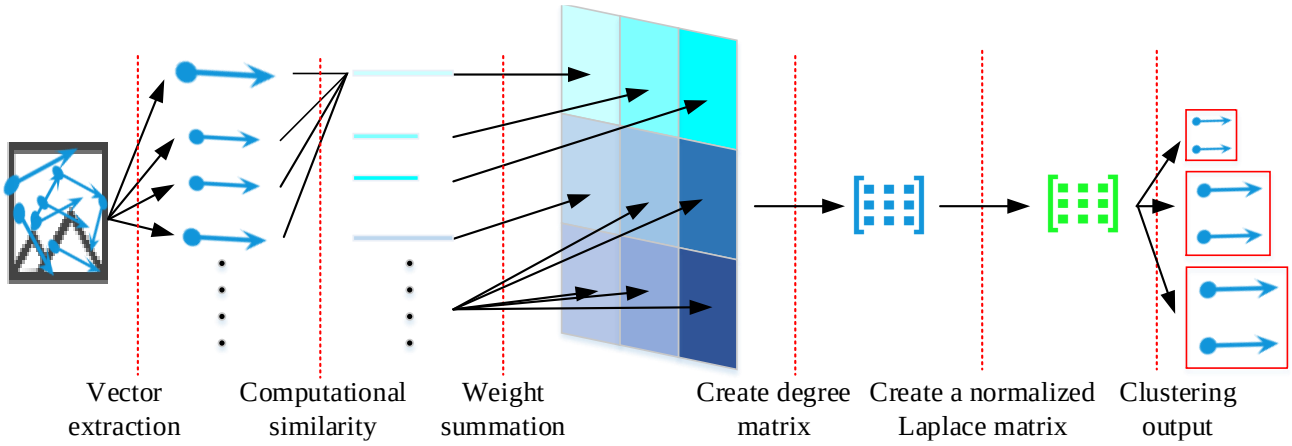


Figure 2: SC algorithm workflow diagram

As shown in Figure 2, before performing clustering analysis, the similarity between vectors is determined by the relationship between them, as calculated in Equation (4).

$$s_{i,j} = \left\| x_i - x_j \right\| \quad (4)$$

In Equation (4), i and j represent two different vectors in the image, $s_{i,j} = \left\| x_i - x_j \right\|^2$ is the Euclidean norm between vectors i and j, and x_i and x_j are the lengths of vectors i and j, respectively. Then, the similarity between the two vectors is determined based on the value of $s_{i,j} = \left\| x_i - x_j \right\|^2$, and the similarity matrix S

is constructed, as shown in Equation (5).

$$\begin{cases} 0, if\ s_{i,j} > \varepsilon \\ \varepsilon, if\ s_{i,j} \le \varepsilon \end{cases} \quad (5)$$

In Equation (5), ε is the specified range radius. If the result is nonzero, it indicates the two vectors are similar. However, binary truncation is too restrictive, so this study uses radial basis function kernel (RBF) instead of binary truncation, combined with adaptive thresholding, to more accurately measure the similarity between text feature vectors. RBF kernel maps feature vectors to high-dimensional space and calculates their similarity, as shown in Equation (6).

$$Sim(x_i, x_j) = \exp\left(-\frac{\left\| x_i - x_j \right\|^2}{2\sigma^2} \right) \quad (6)$$

In Equation (6), x_i and x_j are text feature vectors. σ is the kernel width, which controls the decay rate of similarity. Then, dynamically adjust the threshold θ of the similarity matrix, as shown in Equation (7).

$$\theta = \mu + k\chi \quad (7)$$

In Equation (7), μ and χ are the mean and standard deviation of the feature vector length, respectively. χ is the adjustment coefficient. By adaptively adjusting the threshold of the similarity matrix, it is possible to better cope with datasets of different types and sizes, and improve the accuracy and robustness of clustering. Afterwards, the degree matrix D is created based on the sum of the weights of each vector with other vectors in the S matrix, as calculated in Equation (8).

$$D_{ij} = \sum_{j=1}^{n} S_{ij} \quad (8)$$

In Equation (8), S_{ij} represents the similarity weight of a specific vector in the S matrix. In the degree matrix D, the value of each vector is the sum of the weights of all other vectors in the range ε. Then, the Laplacian matrix of D is computed and normalized, as shown in Equation (9).

$$\begin{cases} L = D - S \\ L' = D^{-1}L \end{cases} \quad (9)$$

In Equation (9), L is the Laplacian matrix, and L' is the normalized Laplacian matrix. The eigenvectors corresponding to the eigenvalues of the normalized matrix are then used as samples for classification, yielding the final multidimensional classification samples. In large-scale text data, sentence length is a simple and low-cost feature that requires minimal preprocessing, and can partly reflect the information content and complexity of the text. Therefore, when implementing spectral clustering, this study chose sentence length as the key classification feature. Divide the text into three clusters based on sentence length: short text (no more than 15 words), medium text (16-40 words), and long text (more than 40 words). In short texts, higher weights are assigned to the beginning and end positions of sentences. In long texts, nouns are given higher weights and verbs are given lower weights. Implement TF-IDF smoothing for medium text to avoid distortion of short sentence frequency. This classification ensures that the TextRank-LP weight calculation shown in equation (2) is performed within the same sentence structure, eliminating statistical distribution differences across length texts. Finally, the SC algorithm is integrated with TextRank-LP to form the TS algorithm, with the specific process shown in Figure 3.

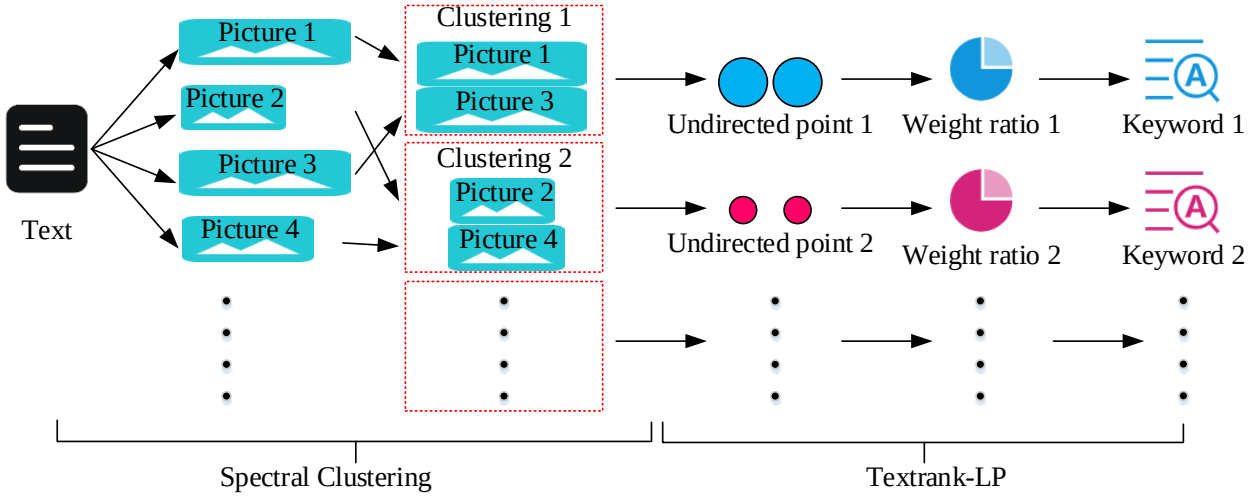


Figure 3: TS algorithm keyword extraction flow chart

As shown in Figure 3, the TS algorithm first performs text preprocessing. Secondly, use the SC algorithm to cluster text fragments. Then, treat each word as a node in the graph and use TextRank-LP to calculate the weight of each node. Subsequently, the results of spectral clustering are combined with the weight calculation of TextRank-LP to obtain the final comprehensive weight, and keywords are extracted based on the weight size. Finally, sort the keywords based on their comprehensive weights and output a list of keywords.

3.2 Construction of neural network-based public opinion research model

However, the TS algorithm can only extract keywords, and a complete study of public opinion evolution requires additional processes such as monitoring range division and data analysis [19]. Therefore, the study proposes an emergency online public opinion monitoring process with the TS algorithm as the keyword extraction module. The specific steps of this process are shown in Figure 4.

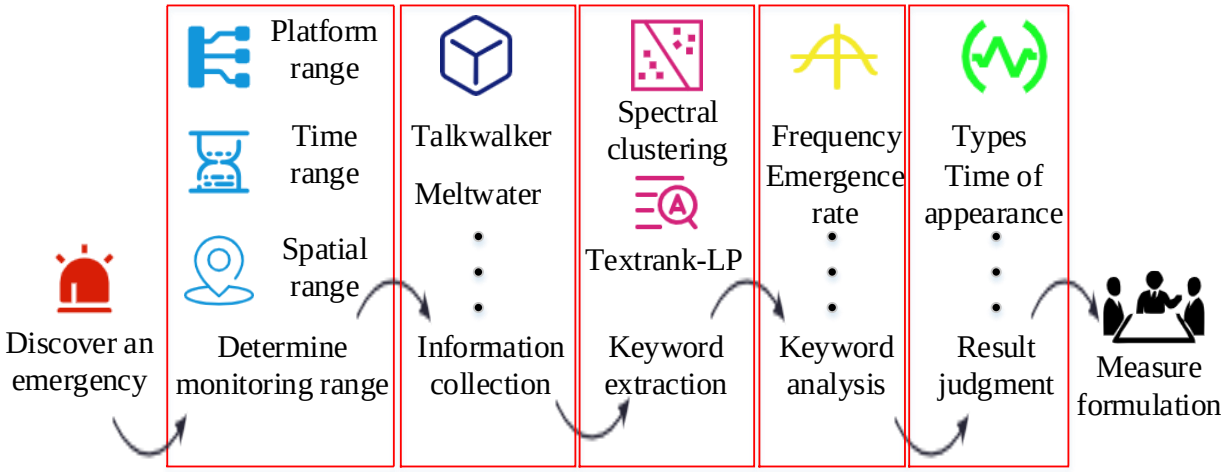


Figure 4: Emergency online public opinion monitoring process

As shown in Figure 4, before keyword extraction, the monitoring range is determined. Then, computer software is used to collect online texts from different channels. Next, the TS algorithm is applied to extract keywords, identifying frequently occurring and widely covered words as keywords. To grasp the development trend of emergency online public opinion, the properties of these keywords and their appearance speed are further analyzed. TDNN captures local contextual changes, while LSTM networks effectively process time-series information and capture global changes [20]. Therefore, to better grasp the temporal changes of keywords, the research integrates TDNN and LSTM to create a keyword analysis network that combines the advantages of both. The structure of this network is shown in Figure 5.

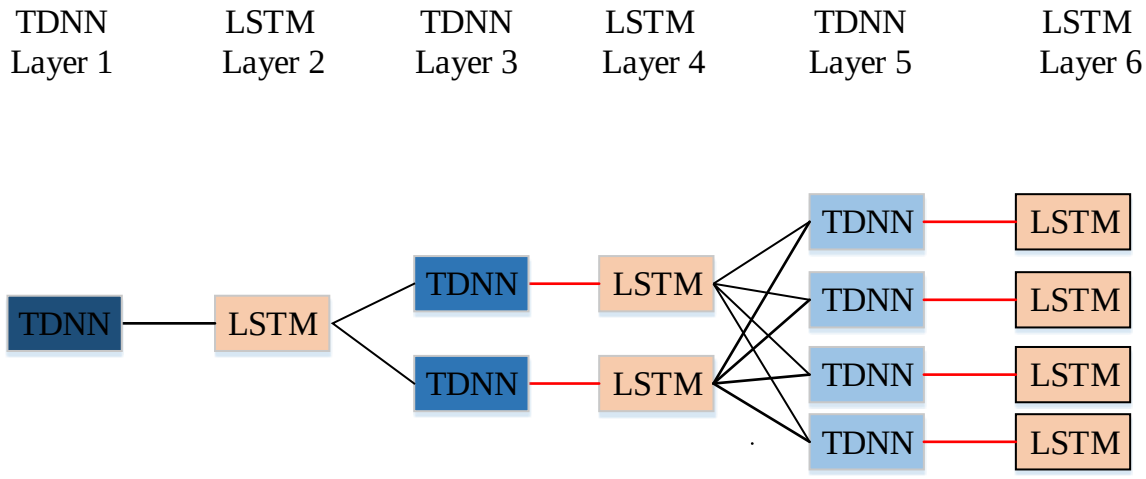


Figure 5: Structure diagram of TDNN-LSTM network

As shown in Figure 5, the TDNN-LSTM network is formed by connecting TDNN and LSTM sequentially, and belongs to a many to one time series model. It includes 6 hidden layers, among which the 1st, 3rd, and 5th layers are TDNN structures. The second, fourth, and sixth layers are LSTM structures, with each TDNN and LSTM layer containing 512 nodes. The input layer of TDNN-LSTM receives time series data with a length of T, and the feature dimension of each time step is D. After multiple layers of processing, it outputs the prediction result of a single time step. Using the Adam optimizer, the learning rate parameter is set to 0.001 and adjusted based on changes in loss during training, using Mean Squared Error (MSE) as the loss function. The output of a single TDNN neuron is represented in Equation (10).

$$h(t) = f(\sum_{n=1}^{N}[w_n * x(t+n) + b]) \quad (10)$$

In Equation (10), f is the activation function, N is the total time the information stays in that layer, t represents the input time, n is the time step, w_n is the weight for different time steps, and b is the bias. The total output of each layer neuron is represented in Equation (11).

$$h(t) = f(\sum_{m=1}^{M}\left[\sum_{n=1}^{N} win * x_m(t+n) + b_m\right]) \quad (11)$$

In Equation (11), M is the total number of neurons in the layer, x_m represents the m-th neuron, and b_m represents the bias of the m-th neuron. Then, the LSTM subunit processes the short-sequence features from the TDNN layer, extracts the dependency relationships between different short-sequence feature segments, and stores and outputs the features with higher correlations. The computational process for the forget gate, input gate, and output gate of the LSTM subunit is shown in Equation (12).

$$\begin{cases} f_t = \sigma(w_f \bullet (h_{t-1}, x_t) + b_f) \\ i_t = \sigma(w_i \bullet (h_{t-1}, x_t) + b_i) \\ o_t = \sigma(w_o \bullet (h_{t-1}, x_t) + b_o) \end{cases} \quad (12)$$

In Equation (12), h_{t-1} is the previous time output state, and x_t is the current time input. σ is the activation function. w_f, w_i, and w_o are the forget, input, and output gate forget weights, while b_f, b_i, and b_o are the neuron biases for the corresponding layers. f_t, i_t, and o_t are the output data for the corresponding layers. The data is output by the output gate, and the internal data of the LSTM subunit is fully updated, as shown in Equation (13).

$$C_t = f_t \bullet C_{t-1} + [\tanh(w_c \bullet (h_{t-1}, x_t) + b_c)] \bullet i_t \quad (13)$$

In Equation (13), C_{t-1} represents the state of the neuron before the update, and C_t represents the updated state. The final output of the neuron requires activation using the tanh function, as shown in Equation (14).

$$h_t = o_t \bullet \tanh(C_t) \quad (14)$$

In Equation (14), h_t refers to the final output of the memory cell at time t. By combining the keyword extraction advantage of the TS algorithm with the powerful time-series correlation processing ability of the TDNN-LSTM network, the study constructs the TSTL model. The model structure is shown in Figure 6.

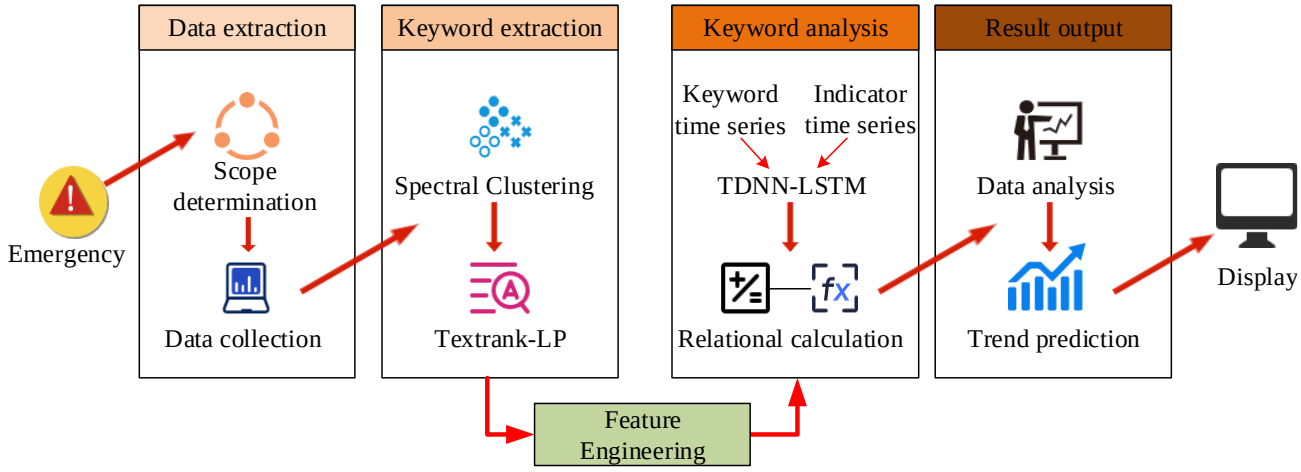


Figure 6: Workflow diagram of TSTL model for online public opinion research

As shown in Figure 6, in the TSTL model, the first step is to perform clustering analysis on the text from various network environments, a process completed by the SC algorithm in the model. Next, keyword extraction is carried out, performed by the TextRank-LP part, which fully considers factors such as word type and position. The TDNN-LSTM network is then used to analyze the time-series relationships, such as the occurrence time of keywords. The input of the TDNN-LSTM network includes two parts: keyword time series and exported indicator time series. In this process, the study selects the propagation speed, attention, and dissent ratio of texts with keywords as the distinguishing criteria. The calculation of the propagation speed is shown in Equation (15).

$$sp = \frac{\Delta R}{\Delta t} \quad (15)$$

In Equation (15), ΔR represents the change in reading volume per unit time, and Δt represents the time unit. The faster the propagation speed, the more likely it is for a network public opinion event to occur. The process for calculating attention is shown in Equation (16).

$$A = \alpha * r + \beta * d + \gamma * c \quad (16)$$

In Equation (16), α, β, and γ are the weight coefficients, while r, d, and c represent the reading volume, transmission volume, and comment volume, respectively. The larger the attention, the more likely it is for a network public opinion event to occur. The method for calculating the dissent ratio is shown in Equation (17).

$$R = \frac{V_n}{V} * 100\% \quad (17)$$

In Equation (17), V and V_n represent the total voice and the non-mainstream voice, respectively. A larger dissent ratio indicates a greater divergence within the public. The final model uses the temporal variations of these parameters to predict whether a network public opinion event will occur during an emergency.

4 Validation of emergency online public opinion research model

4.1 Keyword extraction performance verification of TS algorithm

To evaluate the performance of the TS algorithm, the study used the Natural Language Processing and Chinese Computing (NLPCC) dataset for testing. The NLPCC dataset, constructed by the Chinese Information Society, is a Chinese natural language processing evaluation dataset, which contains a large amount of data for tasks such as sentiment analysis and text summarization. This study used NLPCC2014 Task 2, an open-source dataset obtained through the official website of the Chinese Information Society, including 5000 positive and negative training samples and 1250 positive and negative testing samples. Term Frequency-Inverse Document Frequency (TF-IDF), Bi-LSTM, and Support Vector Machine (SVM) were used as comparison models to verify the effectiveness of the proposed algorithm in keyword extraction. All algorithms were run under the same conditions during the experiment. The experimental settings are shown in Table 2.

Table 2: Experimental settings and configurations

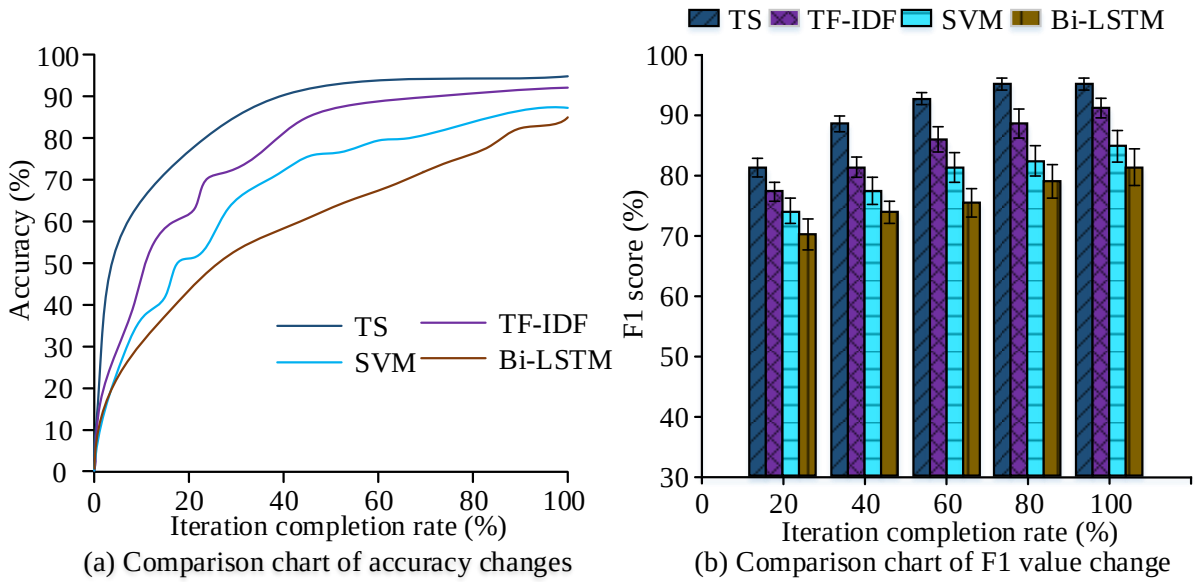
/	Category	Version	Category	Version
Software	Operating system	Windows 11	Deep learning framework	PyTorch 2.1
	Programming language	Python 3.8	Visualization library	Mtplotlib
Hardware	CPU	Ryzen 7 9800X3D	GPU	NVIDIA RTX 3080
	Memory	64GB RAM	Storage	128 GB SSD

To quantify the accuracy of SC algorithm pre-classification, the study used clustering purity to evaluate the length classification effect. The experiment used 5000 texts from the NLPCC dataset, labeled as 1520 short texts, 2480 medium texts, and 1000 long texts according to their actual lengths. The confusion matrix between the pre classification results of the SC algorithm and the real labels is shown in Table 3.

Table 3: Confusion matrix between pre classification results of SC algorithm and real labels

Real category	Prediction category			Recall/%
	Short text	Medium Text	Long Text	
Short text	1385	1335	0	91.1
Medium Text	98	2252	130	90.8
Long Text	0	95	905	90.5
Precision/%	93.4	86.9	87.6	-

From Table 3, it can be seen that the SC algorithm pre classification can accurately separate texts of different lengths, with a recall rate of over 90%. After calculation, the clustering purity is 89.6%, indicating that the SC algorithm achieves better clustering performance. First, to verify the learning capability of the TS algorithm, the NLPCC dataset was used to train the algorithm iteratively. The accuracy and F1 score changes during the iteration were compared and analyzed. The results are shown in Figure 7.



(a) Comparison chart of accuracy changes (b) Comparison chart of F1 value change

Figure 7: Comparison of accuracy changes and F1 values of each model

As shown in Figure 7(a), at the end of the iteration, the accuracy of the TS algorithm was the highest at 95.1%, while the TF-IDF algorithm achieved 92.1%, SVM 88.1%, and Bi-LSTM network 86.0%. Additionally, the TS algorithm started to converge at 40% of the iteration, earlier than the comparison algorithms. This indicates that the TS algorithm has the strongest learning ability and higher learning efficiency. As shown in Figure 7(b), with the increase in the iteration rate, the F1 score of the TS algorithm increased from 81.5% to 94.6%. The TF-IDF algorithm increased from 78.1% to 92.0%, SVM from 74.5% to 86.0%, and the Bi-LSTM network from 70.3% to 81.2%. This shows that the TS algorithm has stronger classification ability. Next, to verify the work efficiency of the TS algorithm, the text processing speed of each algorithm was compared. The results are shown in Figure 8.

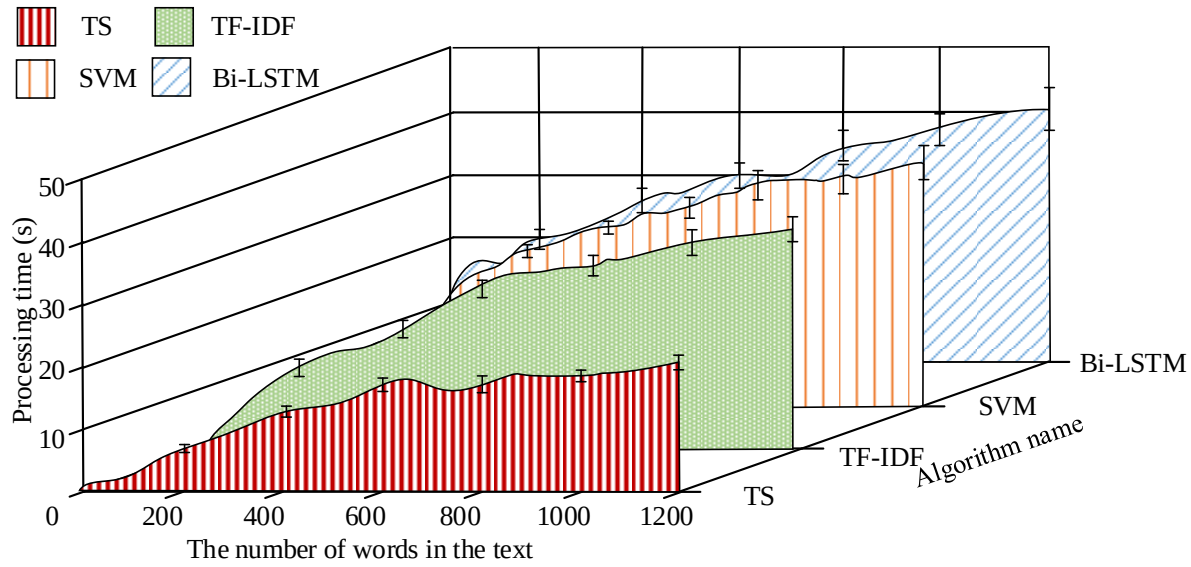


Figure 8: Comparison of processing time for texts of different lengths

As shown in Figure 8, all algorithms exhibited an increasing processing time as the text length increased. However, for all text lengths, the TS algorithm took less time than the comparison algorithms. When the text length was 600 characters, the processing time of the TS algorithm was 17s, while the TF-IDF algorithm took 20s, SVM took 23s, and the Bi-LSTM network took 30s. When the text length was 1200 characters, the processing time of the TS algorithm was 20s, while the TF-IDF algorithm took 29s, SVM took 30s, and the Bi-LSTM network took 40s. In conclusion, the TS algorithm exhibited high efficiency in keyword extraction for texts of various lengths. To verify the accuracy of keyword extraction by the TS algorithm, the recognition results of each algorithm were compared. The results are shown in Figure 9.

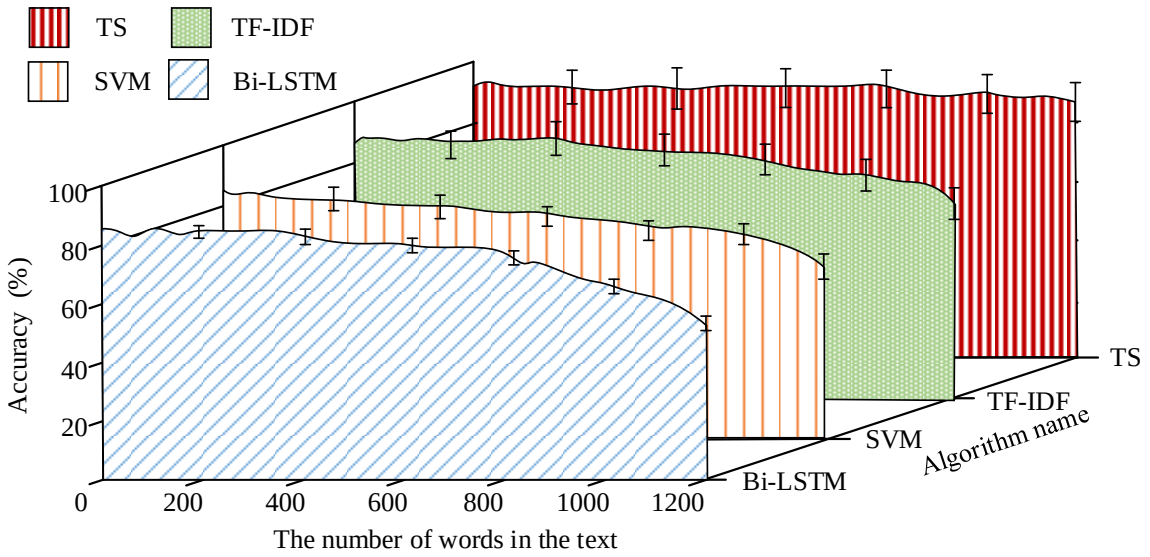


Figure 9: Comparison of keyword extraction accuracy for texts of different lengths

As shown in Figure 9, all algorithms showed a trend where accuracy decreased as text length increased. However, for all text lengths, the TS algorithm had a higher accuracy than the comparison algorithms. When the text length was 400 characters, the accuracy of the TS algorithm was 93.1%, while the TF-IDF algorithm's accuracy was 90.1%, SVM's accuracy was 82.3%, and the Bi-LSTM network's accuracy was 78.2%. When the text length was 1200 characters, the accuracy of the TS algorithm was 90.1%, while the TF-IDF algorithm's accuracy was 76.8%, SVM's accuracy was 63.2%, and Bi-LSTM's accuracy was 54.5%. In conclusion, the TS algorithm had a higher accuracy in keyword extraction for texts of different lengths.

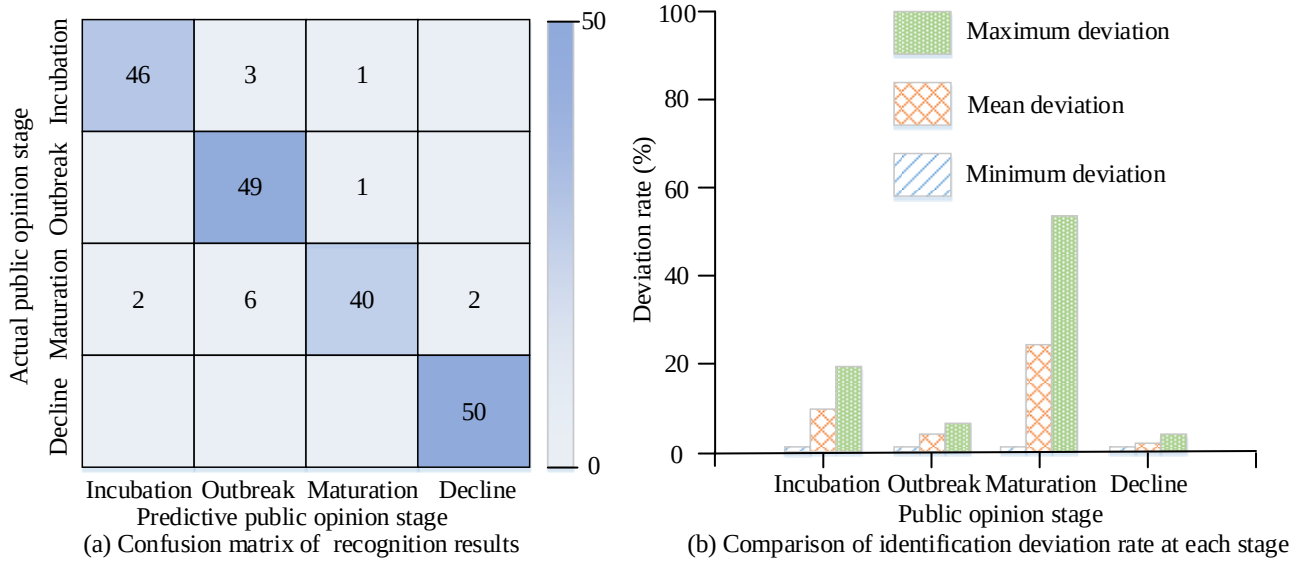
4.2 Practical application test of TSTL model

The 2019 NBA and China controversy event-related data was used as the dataset. The data mainly comes from Weibo. This study collected relevant information from public social media platforms through web crawling technology, strictly following the platform's terms of use and laws and regulations during the collection process. The total monitored public opinion information was 2538. Firstly, perform data preprocessing by using text similarity clustering methods to remove a large amount of duplicate or highly similar content. Using keyword filtering and sentiment analysis techniques, select data that is directly related to NBA China and has clear emotional tendencies. Useless characters, HTML tags, etc., were removed, and encoding issues and typos in the text were corrected. Divide the dataset into a training set (70%), a validation set (15%), and a testing set (15%). Determine hyperparameters through grid search. Set the time step of TDNN to 3, initialize the forget gate bias to 1.0, set Dropout to 0.2, set L2 regularization to 0.01, set the initial learning rate to 0.001, set the batch size to 32, and set the training epochs to 100. Choose the Adam optimizer, set the initial learning rate to 0.001, and decay by 0.1 times every 10 epochs. If the performance of the validation set does not improve for 10 consecutive epochs, stop training and use 5-fold cross validation to ensure model stability and reliability. Compare the complete TSTL model with TDNN-LSTM, TextRank-LP-TDNN-LSTM, TS-TDNN, and TS-LSTM. The results of the ablation experiment are shown in Table 4.

Table 4: Results of ablation experiment

Model	Accuracy/%	F1/%	Cohen's Kappa
TDNN-LSTM	90.22	89.82	84.63
TextRank-LP-TDNN-LSTM	93.46	92.57	86.59
TS-TDNN	87.49	86.04	84.25
TS-LSTM	89.24	88.62	84.15
TSTL	95.18	94.61	90.45

From Table 4, it can be seen that the indicators of the complete TSTL model perform the best, with an accuracy of 95.18%. This indicates that the proposed improvement strategies effectively enhance the model's public opinion prediction performance. Use TF-IDF, Bi-LSTM, and SVM as comparison models. To verify the TSTL model's ability to recognize network public opinion risk states, 200 sets of public opinion information from the 2019 NBA period were extracted. This included 50 sets each from the incubation period, outbreak period, maturation period, and decline period, as shown in Figure 10.



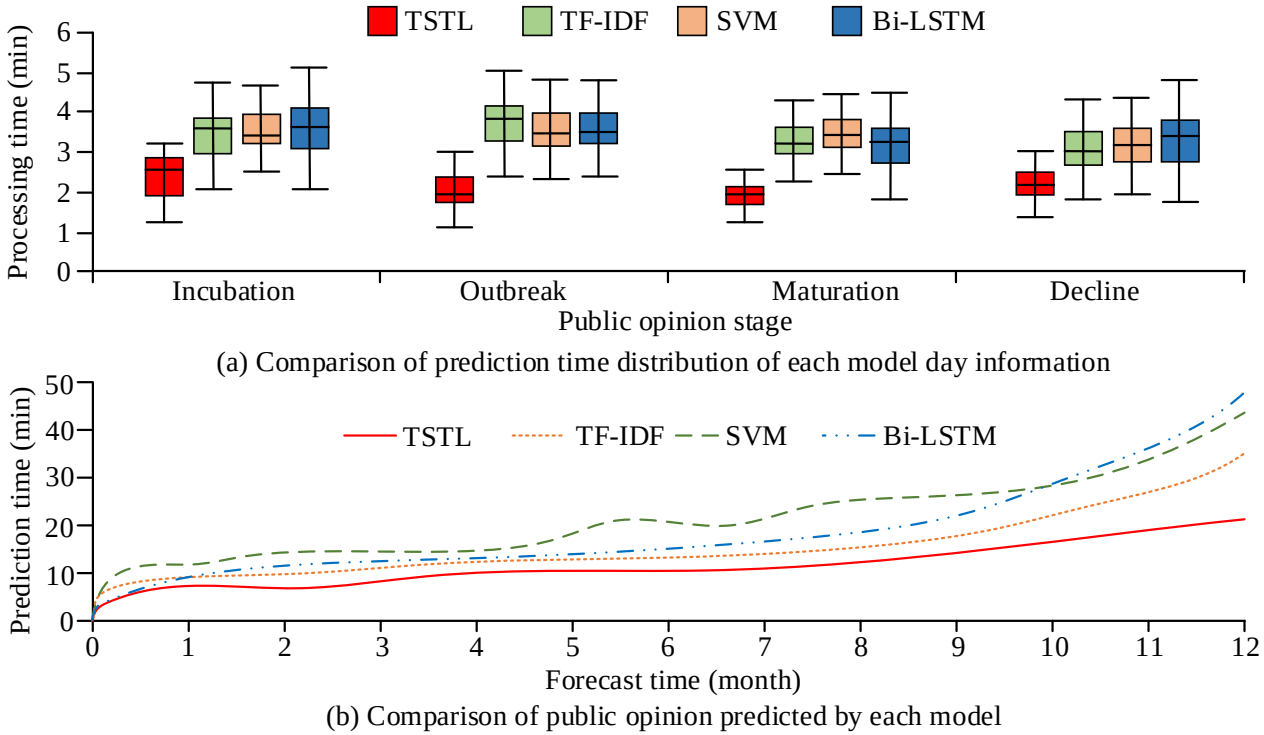
(a) Confusion matrix of recognition results

(b) Comparison of identification deviation rate at each stage

Figure 10: Confusion matrix and relative deviation rate of recognition results

As shown in Figure 10(a), in the data from the four different stages, the TSTL model had a recognition accuracy of 100% for the decline period data, 80% for the maturation period, 98% for the outbreak period, and 92% for the incubation period. The average accuracy was 92.5%. As shown in Figure 10(b), the maximum deviation for the maturation period data was 55.2%, with an average of 21.0%, both higher than the other stages. In

contrast, the maximum deviation for the decline period was only 3.2%, with an average of 1.5%, both lower than the other stages. This indicates high model accuracy in identifying public opinion stages, with highest recognition accuracy during the decline period. The TSTL model runs on GPU and utilizes 24 threads to accelerate data preprocessing and model inference. The Bi LSTM model runs on GPU and is single-threaded. The TF-IDF model and SVM model run on the CPU, single-threaded. The average GPU utilization rates of the TSTL model and Bi LSTM model are 85% and 70%, respectively. The average CPU utilization rates of TF-IDF and SVM models are 60% and 55%, respectively. To verify the work efficiency of the TSTL model, the processing time for 200 sets of data was compared across models, and the time spent for predicting future public opinion states was also compared. The results are shown in Figure 11.



(a) Comparison of prediction time distribution of each model day information

(b) Comparison of public opinion predicted by each model

Figure 11: Comparison of processing time and prediction time

As shown in Figure 11(a), regardless of the public opinion stage, the TSTL model's processing time was generally lower than the comparison models. The time distribution for the outbreak, maturation, and decline periods had lower dispersion compared to the comparison models. As shown in Figure 11(b), under different future prediction durations, the TSTL model required less time than the comparison models. For instance, when predicting for 12 months, the TSTL model took 21 minutes, the TF-IDF model took 32 minutes, the SVM model took 43 minutes, and the Bi-LSTM model took 47 minutes. This indicates that the TSTL model was faster in both current data processing and future public opinion prediction. Finally, to verify the accuracy of the model in actual applications, the predicted changes in attention from each model were compared with the actual changes in attention. The results are shown in Figure 12.

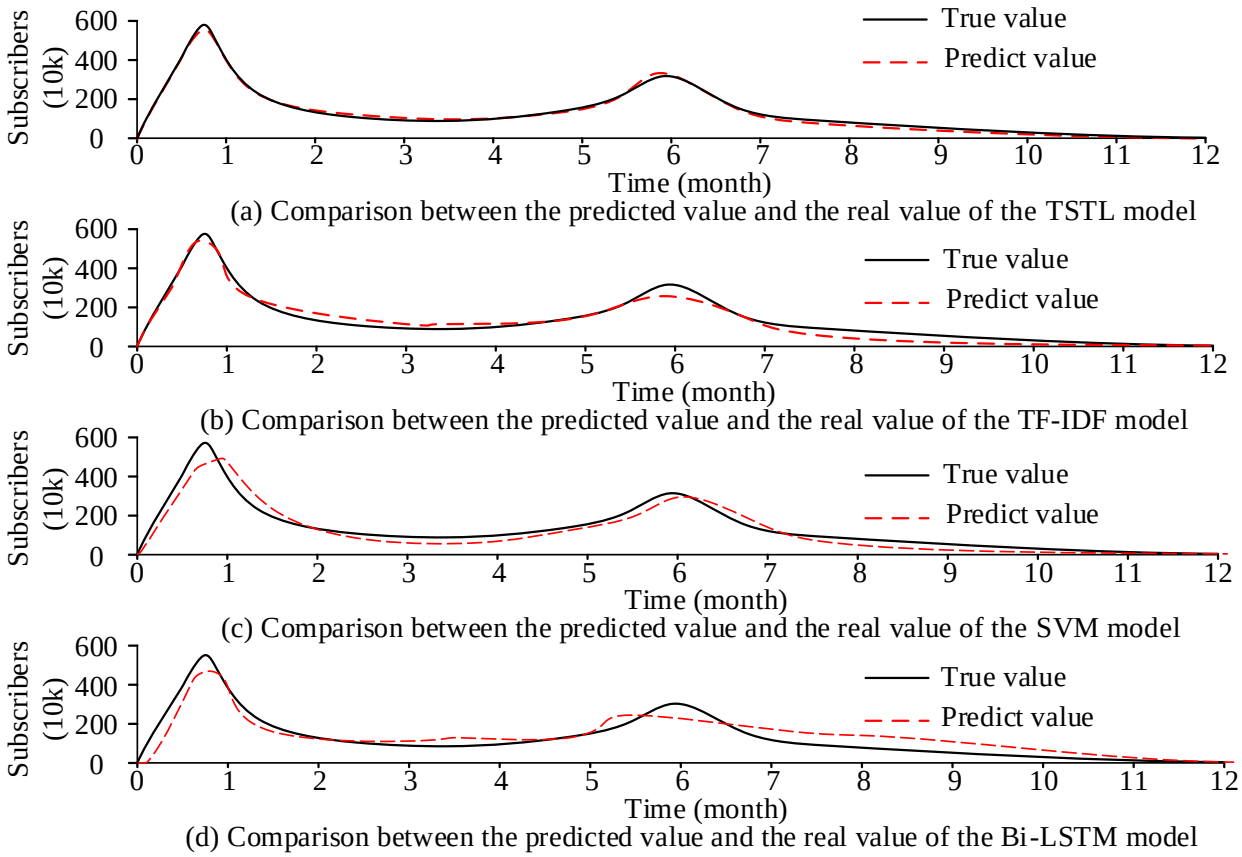


Figure 12: Comparison of predicted attention and actual attention

As shown in Figure 12(a), the predicted attention of the TSTL model was closely aligned with the ground truth, with only slight deviations at 1 month and 6 months after the public opinion event occurred. As shown in Figure 12(b), the TF-IDF model's prediction had significant deviations at 1 month and 6 months, with slight deviations at months 2-4 and 7-9. As shown in Figures 12(c) and 12(d), the predictions of the SVM and Bi-LSTM models had large deviations from the actual results, with the first predicted outbreak occurring 0.1-0.2 months later than the actual event, and the predicted attention scale was clearly smaller than the actual scale. In conclusion, the TSTL model had superior prediction capability for future public opinion compared to the TF-IDF, SVM, and Bi-LSTM models. To further validate the proposed model's superiority and generalization, this study used ICE-2024 international event data for testing, including 8426 data points. Compare the proposed TSTL model with the currently advanced Robust Optimized BERT Approach (RoBERTa), Multi Task Learning Deep Feedforward Sequential Memory Network (MTL-DFMN), and Modern Temporary Convolutional Network (ModernTCN). Accuracy, mean square error (MSE), and mean absolute error (MAE) are used as evaluation metrics. Repeat the experiment 10 times to obtain stable statistical results, and use paired t-test to evaluate whether the performance differences between models are statistically significant. Set the significance level α to 0.05, and if $p<0.05$, it is considered significant. The performance comparison results of the four models are shown in Table 5.

Table 5: Performance comparison of four models

Model	Accuracy/%	MSE	MAE	p (vs. ModernTCN)
RoBERTa	93.052±1.761	0.028±0.006	0.156±0.075	<0.05
MTL-DFSMN	91.680±2.042	0.032±0.011	0.178±0.082	<0.05
ModernTCN	92.638±1.850	0.029±0.008	0.163±0.077	<0.05
TSTL	95.125±1.043	0.021±0.005	0.131±0.062	-

From Table 5, it can be seen that the proposed TSTL model still demonstrates good performance in the larger ICE-2024 international event data, with an average accuracy of 95.125%, MSE of 0.021, and MAE of 0.131, which is significantly better than the comparison model ($p<0.05$). The results indicate that the proposed TSTL

model demonstrates superior performance and good generalization in public opinion analysis tasks.

5 Discussion

To address low efficiency and poor predictive ability in current keyword extraction and online public opinion evolution research methods, the study proposed a network public opinion evolution research model based on TextRank-LP. This model uses an optimized TextRank-LP for keyword extraction and integrates TDNN and LSTM networks as the data analysis module to perform time-series feature analysis of online public opinion. In the process of keyword extraction, the SC algorithm classifies the text based on the text feature vector, reducing the weight propagation bias in the keyword extraction process, and the classified text has clearer information structure, improving keyword extraction speed. In addition, by using features such as sentence length as classification criteria, texts within the same cluster have similarity in sentence structure, further improving the accuracy of TextRank-LP in weight assignment. The experimental results show that the accuracy of TF-IDF, SVM, and Bi-LSTM algorithms is 92.1%, 88.1%, and 86.0%, respectively. The accuracy of the TS keyword extraction algorithm proposed in the study can reach 95.1%, which is higher than the comparison algorithm, and it begins to converge at an iteration completion rate of 40%. When the text length is 1200 words, the processing time of the TS algorithm is 20 seconds, which is 9 seconds shorter than the TF-IDF algorithm. This verifies the positive impact of SC pre-classification on keyword extraction. In practical testing of the constructed TSTL model, the recognition accuracy for public opinion stages was 92.5%. The model demonstrated superior processing efficiency. In addition, when analyzing the temporal variation relationship of keywords, TDNN is mainly used to extract local time series features and capture short-term dependencies through convolution operations. LSTM networks have unique memory units and gating mechanisms, which can effectively handle dependencies over long time spans. In the TSTL model, the combination of TDNN and LSTM enables the model to grasp both the local variation characteristics of keywords and the global temporal relationships. The experimental results show that the TSTL model can more accurately predict the future development of public opinion in public opinion prediction experiments, and can accurately predict network public opinion attention 12 months ahead within 21 minutes. This is due to the strong sensitivity of LSTM to sequences, which can better grasp the temporal changes of keywords.

Data bias may have a significant impact on the performance and results of the model. If there are deviations in the data collection process, the model may not be able to fully reflect the actual situation of the entire public opinion, resulting in deviations in predicting the development of public opinion and identifying key features. The complexity and diversity of language can also lead to semantic biases in data. Therefore, in practical applications, continuous monitoring and evaluation of data quality are necessary to ensure the reliability and effectiveness of the model. The TextRank-LP-based network public opinion evolution model has good scalability and can handle high-capacity multi-platform text streams. In practical applications, distributed computing and data preprocessing techniques can meet high-capacity multi-platform text stream processing requirements. Meanwhile, by optimizing the architecture of the model, such as adopting more efficient neural network structures and optimization algorithms, the running speed and efficiency of the model can also be improved, enabling it to better adapt to complex network environments. In addition, the model is constructed based on TextRank-LP and TDNN-LSTM networks, and has strong generalization ability, thus exhibiting certain advantages in transferability across event types. Specifically, the TextRank-LP algorithm does not rely on domain specific knowledge and mainly focuses on the structure of the text and the importance of words when extracting keywords, making it applicable to different types of events. The TDNN-LSTM network can adapt to changes in different time series characteristics, thus accurately grasping the evolution law of public opinion in different types of events. Although there are differences in the data characteristics of different event types, the model can adapt to these differences by adjusting parameters and training processes.

6 Conclusion

In conclusion, the TextRank-LP and TDNN-LSTM network-based model for keyword extraction and evolution of public opinion in emergency events demonstrated high accuracy and efficiency, meeting the accuracy and efficiency requirements for emergency event public opinion research. The proposed model has broad prospects in practical applications, not only for monitoring public opinion, but also for promoting business development. For example, when monitoring social media public opinion during the release of a brand’s new product, the model can quickly extract key information, thereby helping the enterprise to understand the stage of public opinion in real time and adjust market strategies in a timely manner. However, the actual network environment is much more complex than the laboratory, and the attention-based linear modeling method used in this study may not fully capture subtle nonlinear features of public opinion changes when dealing with complex nonlinear public opinion evolution laws. In addition, the current model only uses sentence length as a text classification criterion, which may be limited when dealing with multilingual and text

containing a large number of informal expressions and slang. Therefore, in future research, cyclic attention mechanisms can be further introduced to better handle complex nonlinear features, such as Transformer models. Additionally, multilingual pre-trained models can be used for initialization to effectively capture common features of different languages, such as mBERT.

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Real-Time Detection of Anomalous Behaviors in Power Systems Using Hidden Markov Models

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With the development of the power industry, ensuring the safety of live work is increasingly vital. However, traditional monitoring methods often struggle to identify and predict this abnormal behavior accurately. Therefore, this paper proposes a new technology to detect abnormal behavior in field work using the hidden Markov model. Introducing the hidden Markov model establishes a dynamic work behavior model to detect abnormal behavior. In the research, the behavior pattern of the field work process is analyzed first, and the factors affecting the change of behavior state are determined. Then, the hidden Markov model is used to build a state transition model of real-time work behavior, and the model is trained and optimized by historical data. The experiment found that the model can capture the dynamic behavior of workers in the field work and predict their next behavioral state. Many experiments and simulation results show that the abnormal behavior detection technology based on Hidden Markov Model can accurately identify abnormal behavior in the work process, provide timely warning, and ensure the safety and efficiency of fieldwork. In addition, the model is robust and scalable and can adapt to different working environments and operator changes. The abnormal behavior detection technology based on the hidden Markov model proposed in this paper not only improves the safety and efficiency of live work but also provides vital support for the sustainable development of the electric power industry. Through experimental verification, the detection accuracy of this method reaches more than 90%, the false alarm rate is controlled within 5%, and the average processing speed is 20 frames per second, which can meet the requirements of real-time detection. These indicators show that the technology has high reliability and effectiveness in the detection of abnormal behavior, and provides strong support for the safe and stable operation of the power system.

Povzetek: Razvit je model za sprotno zaznavo nenavadnih vedenj v energetiki, ki združuje HMM model prehodov stanj z računalniškim vidom in opozarja na kršitve PPE.

1 Introduction

Studies have shown that the correct use of safety protection equipment in power scenarios can reduce the occurrence of deaths caused by falls, slips, trips, or being hit by falling objects. In the United States, half of the casualties at electrical work sites are caused by live workers who do not use personal protective equipment or use it improperly [1, 2]. In 2020, the number of safety accidents and deaths in power construction across the country has increased compared with the previous year. The above phenomena show that some power companies only pay attention to the progress of the construction period and despise the safety and quality, do not have enough safety supervision on the work site, risk prevention and hidden danger investigation have not formed a long-term mechanism and are effectively implemented, and the weak safety awareness of live workers has led to safety accidents on the site. Repeatedly prohibited.

Most of the existing studies deal with the detection of abnormal behavior with low detection accuracy or low calculation efficiency. For example, FGW struggles to accurately identify certain subtle abnormal behaviors in the face of complex homework scenarios, resulting in a detection accuracy of only 72%. And this paper, based on Hidden Markov Model (HMM), through the thorough analysis of operation process and feature extraction, can more accurately capture abnormal behavior pattern, effectively improve the detection accuracy, reached 90%, and by optimizing the algorithm structure to reduce the consumption of computing resources, realize the real-time detection, to make up for the shortage of the existing technology.

As the premise of live work, safe production is an important guarantee to improve the economic benefits of enterprises. The eternal theme of power production and construction is "safety first, prevention first". In the insulation operation method of the power operation scene, thanks to the protection of the insulation protection tool, the live wire will not penetrate the air gap and discharge the human body. Safe distance plays a protective role in indirect live work, and it will be very

dangerous to lose its protection [3, 4]. In 10KV distribution network, the minimum safe working distance between the operator and the live body is 0.7m3. When the live workers do not wear safety protection equipment correctly or the distance between them and the live body is less than the safe distance, the personal safety of the workers will be threatened. Nowadays, video surveillance is generally installed on the operation site of the power industry to supervise production activities through manual observation of video. Due to the wide space range of the power scene, the large number of live workers, the diversity and complexity of the operation behavior, it is often necessary for the relevant staff to watch the surveillance video continuously and alarm the abnormal phenomena found, which can easily cause fatigue and then affect the processing efficiency. In summary, manually assessing whether live workers adhere to regulations poses a significant challenge, and any errors made can have a direct and immediate impact on the personal safety of those workers.

In recent years, the advent of big data and high-performance computing has spurred the rapid evolution of deep learning, paving the way for the industrialization of computer vision solutions rooted in this technology [5, 6]. The application of intelligent monitoring based on computer vision in the power industry can effectively improve the intelligent level of the power supervision system. In recent years, China's power grid has gradually begun to use intelligent video analysis technology based on computer vision to automatically identify and extract key target information from complex video images. This can detect potential safety hazards in power scenarios in a timely manner, complete pre-warning, early processing and later evidence collection, further enrich the functions of video detection, and enhance safety supervision capabilities.

Based on the above background, this paper uses a method based on computer vision and deep learning to complete the tasks of safety protection equipment detection of live workers, personnel posture estimation, safety distance measurement between workers and live bodies, and hand operation state visualization [7, 8]. Through intelligent monitoring technology, real-time alarms notify live workers of safety violations, which can effectively improve the safety supervision capabilities of the work site, reduce the occurrence of safety accidents, and provide strong support for the safety management of power scenarios.

2 Related technology and theoretical basis

2.1 Camera calibration principle

In camera calibration, in order to obtain the corresponding relationship between three-dimensional space coordinates and two-dimensional pixel coordinates, the parameters that need to be used include camera built-in parameters, distortion parameters and external parameters between camera and lidar. To do a good job in the follow-up work, the premise is to ensure the accuracy of camera calibration results first, which is the focus of safe ranging work. The three-dimensional point position in world coordinate system can be transformed into the coordinate position information of the point in the image through the camera matrix. The external parameters represent the rigid transformation from the 3D world coordinate system to the 3D camera coordinate system. The internal parameters represent the projection transformation from the three-dimensional camera coordinates to the two-dimensional image coordinate system.

The traditional camera calibration method uses the calibration objects with known size to establish the point correspondence relationship, calculates the parameters through the algorithm, and is divided into plane and 3D calibration objects [9, 10]. The Tsai two-step and direct linear methods are classical methods.

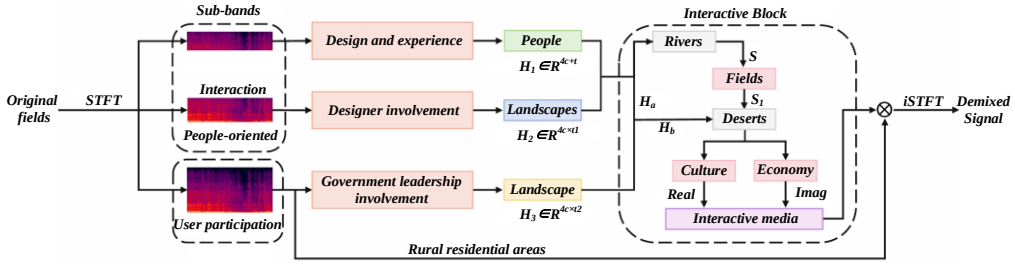

Figure 1: The HMM model construction and initialization process

Figure 1 shows the HMM model construction and initialization process. From the flow chart, we can clearly see the orderly steps of HMM model construction and initialization and the key data information of each link. First, in the state determination stage, five hidden states are identified according to the characteristic analysis of the actual problems. This value is selected through an in-depth study of the data feature distribution and business scenarios, aiming to effectively describe the intrinsic mode of the system with a reasonable number of states. When initializing the observation symbol set, defined 10 different observation symbols, these symbols cover all possible observation situation, through the statistical analysis of a large number of historical data, ensure that the frequency of each symbol is relatively stable, for example, the most common observed symbol probability

of about 0.3, while the rare sign probability around 0.05. The camera self-calibration method is to add some restrictions on camera movement, and establish a relationship Equation between multiple scene images to achieve dynamic on-line calibration of camera parameters. The implementation of this method usually requires the use of parallel or intersecting information in the scene. The representative method is based on vanishing point, which is based on quadratic curve, and has poor robustness and few practical applications.

The camera calibration method based on active vision requires no calibrator, by predetermining and controlling the camera motion information, and then calibrating the scene, establish the corresponding relationship between the collected image data and the target object in the scene [11, 12]. Parameters were calculated from the characteristics of the camera motion. The advantage of obtaining the linear solution and the simple algorithm, but the disadvantage of demanding the experimental conditions and is not suitable when the motion parameters are unknown. In 1998, Professor Zhang proposed the Zhang's calibration method based on the plane checkerboard, which is more accurate than the self-calibration method, and avoids the traditional method requires high precision calibration of objects and tedious operation, and is widely used in machine vision. In this paper, Zhang's calibration method is adopted to establish the relationship between the camera and the image acquisition by locating the checkerboard corner points, and then obtain the internal and external parameters of the camera. In Zhang's camera calibration method, it is necessary to fix the world coordinate system on the checkerboard, and set the physical coordinate W of each point on the checkerboard to 0. This allows the size of each grid in the calibration plate to be determined in advance, and thus the physical coordinates (U, V, W = 0) of each corner in the world coordinate system can be calculated. Then the camera is calibrated by combining the pixel coordinates (u, v) of each point, and the internal parameter matrix and distortion parameters of the camera are obtained.

The steps of camera calibration are as follows: first, the product of the internal parameter matrix is obtained; Secondly, solve the internal matrix; Finally, the outer parameter matrix is solved. If the world coordinate system is fixed on the checkerboard lattice, the physical coordinate W of all points is 0. As shown in Equation (1), it is an imaging model with no distortion at the original single point. Where, the first two columns of the rotation matrix R are r1, r2.

$$s[u,v,1] = A[r_1,r_2,r_3,t][X,Y,0,1] = A[r_1,r_2,t][X,Y,1] \quad (1)$$

Here, the internal parameter matrix is denoted A, as shown in Equation (2):

$$A = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \quad (2)$$

In the Equation, s is the scale factor from the world coordinate system to the image coordinate system; A is the camera internal reference matrix; (u0, v0) is the coordinate of the image principal point; α, β are the fusion of focal length and pixel aspect ratio; y is the radial distortion parameter; R is the rotation matrix; t is a translation matrix.

A [r1, r2, t] is the homograph matrix H, that is, the product of the inner and outer parameter matrices. The three columns [h1, h2, h3] of H are calculated as shown in Equation (3):

$$H = [h_1, h_2, h_3] = A[r_1, r_2, t] \quad (3)$$

H is a 3×3 matrix with one element being a homogeneous coordinate, so H has 8 degrees of freedom. Using 4 corresponding points, 8 degrees of freedom can be obtained, and then the homograph matrix H between the image plane and the world plane can be obtained.

Solve the internal parameter matrix

The following constraints can be obtained from [h1, h2, h3] = A [r1, r2, t]:

Because r1 and r2 are obtained around the x and y axes, respectively, and both the x and y axes are perpendicular to the z axes, r1 and r2 are orthogonal, r1 * r2 = 0.

Since rotation does not change the scale information, the modulus of the rotation vector is 1, that is, r1 = r2 = 1. Based on the above two constraints, h1, h2 can be found from the homography matrix, as shown in Equation (4) and Equation (5):

$$h_1^T A^{(-T)} A^{(-1)} h_2 = 0 \quad (4)$$

$$h_1^T A^{(-T)} A^{(-1)} h_1 = h_2^T A^{(-T)} A^{(-1)} h_2 \quad (5)$$

The next step is to solve the 5 unknown parameters in A. Three homograph matrices can be obtained by taking three pictures in different directions of the same calibration plate, and the unknown parameters in A can be solved by combining the above two constraints. As shown in Equation (6):

$$B = A^{(-T)} A^{(-1)} = \begin{bmatrix} B_{11} & B_{21} & B_{31} \\ B_{12} & B_{22} & B_{32} \\ B_{13} & B_{23} & B_{33} \end{bmatrix} \quad (6)$$

As you can see, B is a symmetric matrix with six valid elements. Let the i-th column vector h = [hi1, hi2, hi3] T in h, then the constraints are shown in Equation (7) and Equation (.8):

$$h_i^T B h_j = v_{ij}^T b \quad (7)$$

$$v_{ij} = [h_{i1}h_{j1} \cdots h_{i1}h_{j2} + h_{i2}h_{j1} \cdots h_{i3}h_{j3} + h_{i1}h_{j3} \cdots h_{i3}h_{j2} + h_{i2}h_{j3} \cdots h_{i3}h_{j3}]^T \quad (8)$$

The above two constraints can be written as homogeneous Equations with respect to b, as shown in Equation (9):

$$v_0 = \frac{B_{12}B_{13} - B_{11}B_{23}}{B_{11}B_{22} - B_{12}^2} \quad (9)$$

2.2 Target detection method

The target detection algorithm can be used to detect the safety protection equipment of live workers in real time. The target detection results can provide relevant auxiliary decision-making information, and then judge whether the personnel wear safety protection equipment correctly, and enhance the safety supervision ability. Target detection can be divided into traditional target detection algorithms and deep learning-based target detection algorithms [13, 14]. The traditional target detection algorithm is more difficult to design, and the extraction of target feature information is not sufficient. The detection accuracy of the algorithm is largely limited by the manual design of feature representation and feature extraction algorithm is reasonable. In contrast, the target detection algorithm based on convolutional neural network has higher accuracy and has become a mainstream algorithm.

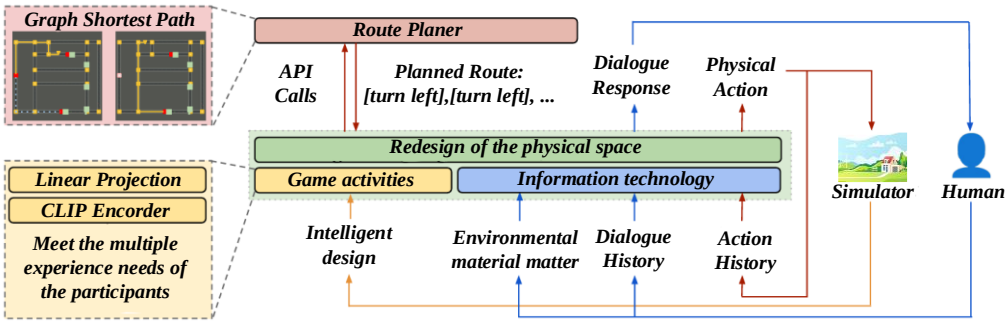

Figure 2: Real-time abnormal behavior detection and response process

Figure 2 shows real-time abnormal behavior detection and response process. From the flow chart, we can understand each link of the whole detection and response process and the corresponding data characteristics in detail. In the data collection stage, video streams are obtained from multiple HD cameras at a rate of 25 frames per second to ensure full coverage of the monitored area and sufficient clarity and detail of the picture, providing a rich information source for subsequent analysis. In the feature extraction process, more than 100 key feature points are extracted for each frame image by specific algorithms. These feature points are trained and screened by a large number of samples, and the representation of abnormal behavior is significantly representative. Entering the abnormal behavior judgment module, the model determines according to the pre-set threshold. When the probability of abnormal behavior exceeds 0.7, it is judged as abnormal. This threshold is verified by repeated experiments, ensuring the high detection rate within 10%. Neural network-based target detection can be divided into two-stage and single-stage target detection. The two-stage algorithm detects the target after extracting the target candidate region, resulting in high model complexity and high computational capacity. In contrast, the single-stage algorithm is simple, significantly improves accuracy and efficiency, and is widely used in industry [15, 16]. The YOLO algorithm proposed by Redmon et al. belongs to the single-stage target detection, which is a breakthrough in real-time target detection. The YOLO algorithm uses the whole image information in the detection process to significantly improve the detection speed, achieve excellent prediction performance, and more accurately distinguish the foreground and background information. YOLO has been continuously iterated and optimized to include YOLOv2, YOLOv3, and YOLOv4. The subsequent YOLOv5, which is more flexible, combines model size and detection speed, and is easy to deploy in embedded devices, is now widely used in industry. The Equations for the hidden Markov model state transition probability and the anomaly score for abnormal behavior detection are shown in (10) and (11).

$$\lambda = B_{33} - [B_{13}^2 + v_0(B_{12}B_{13} - B_{11}B_{23})]/B_{11} \quad (10)$$

$$\beta = \sqrt{\frac{\lambda B_{11}}{B_{11}B_{22} - B_{12}^2}} \quad (11)$$

YOLOv5 CSP (cross-stage part) module is used in the backbone network and Nk to effectively improve the expression ability and training efficiency of the model. The CSP module in the backbone network adopts multiple residual structures, while the CSP module in the Neck part combines convolution and batch normalization operations to enhance the feature fusion ability of the network model. In addition, YOLOv5 introduces the Focus module to divide the high-resolution feature maps into multiple low-resolution feature maps through slice operation to retain the original image information as much as possible and improve the speed of model detection. These variants allow YOLOv5 to achieve a better balance between accuracy and speed for easy user selection.

In contrast, YOLOv5 combines various characteristics of the current model. Its performance is outstanding, and it can take into account both accuracy and speed at the same time. It has become a very frequently used tool in the direction of target detection in various research fields.

2.3 Attitude estimation method

Posture estimation is an algorithm that locates the position information of each body part of the human body and estimates the joint coordinates of the human body after inputting image and video data. Human posture estimation is usually divided into single-person and multi-person posture estimation. Multi-person posture estimation is often used to obtain the coordinates of human joint nodes in power scenes [17, 18]. This section introduces multi-person pose estimation based on monocular images according to two frameworks: top-down and bottom-up.

The top-down attitude estimation framework firstly uses the bounding box of the target detection network to locate all human bodies in the image, and then each person's attitude is predicted by the two-dimensional attitude estimation network, which is shown in Equation (12).

$$u_0 = \frac{\gamma v_0}{\alpha} - \frac{B_{13}\alpha^2}{\lambda} \quad (12)$$

Finally, each key point is accurately located. In the above method, the human body bounding box is used to detect a single human body first, which can reduce the background interference caused by multi-person interaction in the image, and then improve the attitude estimation performance. However, the accuracy of human body detection in the first stage of this method is directly related to the subsequent key point detection, and the key points are often not identified due to personnel missing detection. The computational speed of the method is affected by the number of people in the image [19, 20]. When the number of people in the image increases, the algorithm speed will slow down. The bottom-up attitude estimation framework first obtains all the key points in the picture, which are directly predicted by the key point detection algorithm, and then combines the above key points into the whole human body through matching or clustering algorithms. This algorithm does not need to detect human body, so it has the advantages of fast speed, not affected by the number of people in the picture, and is suitable for real-time multi-person pose estimation. However, when the image illumination, complex background, occlusion and other situations, the detection of key points may be disturbed, resulting in lower positioning accuracy than the top-down algorithm.

4 Power personnel safety monitoring method based on image processing

4.1 Target detection

The data set selected in this study is from the video recording of the live work site of the actual power system, containing 1000 videos of different work scenarios, covering a variety of common live work tasks and possible abnormal behaviors. In the experimental design, data augmentation techniques, including image flipping, rotation, and scaling, are used to expand the dataset scale and improve the generalization ability of the model. The YOLOv5 was chosen as the basic framework of the target detection model because of its high accuracy and fast detection speed in the field of target detection. In terms of parameter tuning, the optimal parameter combination was determined through multiple experimental comparisons, setting the initial learning rate of YOLOv5 to 0.001, momentum to 0.9 and weight attenuation to 0.0005, the selection of these parameters enables the model to converge to better performance faster during training.

The input of the target detection algorithm is the target area picture captured by the visible light camera of the photoelectric pod, and the output is the boundary box and its type information of the target object existing in the picture. At present, this paper can realize the detection of the following target objects: personnel, human head wearing safety helmet, exposed human head, insulating gloves, exposed human hands, safety jacket, ordinary jacket, operating lever and insulating blanket.

In the current mainstream single-stage target detection network, YOLOv5 has a good balance between detection accuracy and reasoning speed. In order to meet the needs of edge computing deployment, this paper adopts YOLOv5 target detection network.

In the preparation of the data set, this topic organizes manpower to simulate live work scenes and shoot videos by wearing complete protective clothing, helmets and other protective equipment, and holding a joystick. The shooting material covers various lighting conditions such as indoor and outdoor, and includes the situation of wearing and taking off various safety protection equipment to simulate safety violations. On this basis, the data of 2000 pictures actually collected in the power field are added. In summary, the dataset contains a total of 5,920 pictures. In this paper, relabeling is used to label the operating lever and insulation blanket in a rotating frame. Since the live workers are inside the lifting platform and the lower body is hidden, the training set does not collect the clothes of the lower body of the live workers. In this paper, the data set is divided into training set, verification set and test set according to the ratio of 4: 2: 1, and the training set is expanded by using the data enhancement tool set of YOLOv5. The data enhancement methods used in this paper are shown in Table 1. After data enhancement, the number of training set pictures is expanded to 16413.

Table 1: The data augmentation method used in this paper

Name	Principle
Mosaic data enhancement	A new picture is obtained by splicing four pictures in the dataset, and the picture is kept All target bounding boxes for the original four pictures
Affine Matrix Data Enhancement	By translating, scaling, rotating and flipping, the original image is transformed by affine transformation

Mix-up data enhancement	A new picture is obtained by mixing different original pictures;

An ideal target detection model requires that the accuracy and recall of the model are very high, approaching 1, and can locate all targets with high accuracy. However, in reality, a model with a high recall rate often exhibits a lower accuracy rate, and the inverse is also true. Consequently, to comprehensively assess the algorithm model by combining the recall rate and accuracy rate, one can plot the Precision-Recall (P-R) curve of the model, using the recall rate as the abscissa and the accuracy rate as the ordinat.

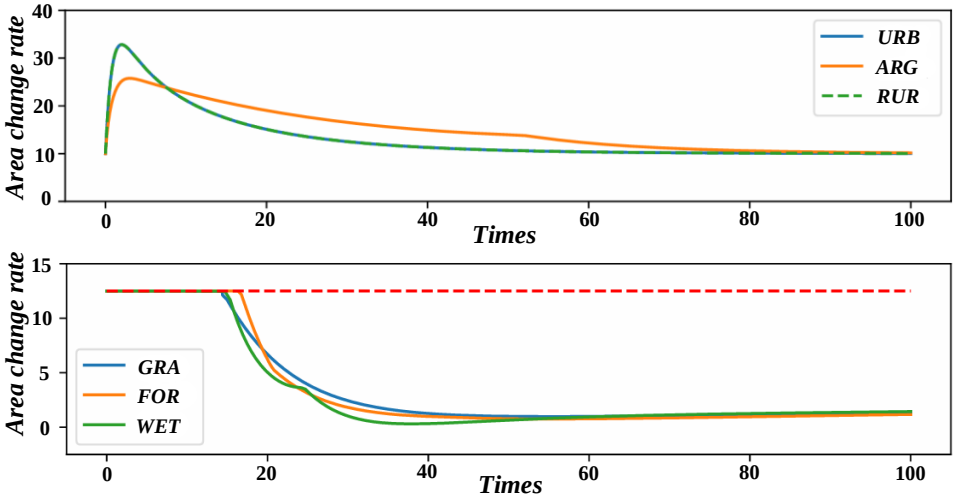

Figure 3: Comparison of the model performance under different HMM parameters

Figure 3 shows comparison of the model performance under different HMM parameters. From the figure, it is clearly seen from the data graph that the model performance showed significant differences as the HMM parameters change. In terms of accuracy, when the parameter is set to 0.008, the model accuracy reaches 80%, and then the model can classify the samples more accurately. However, when adjusted to 0.005, the accuracy increased to 88%, indicating that this parameter adjustment makes the model capture the data features more accurately and reduces misjudgment. However, when the parameter was further changed to a momentum of 0.004, the accuracy decreased to 75%, perhaps because the overcomplex parameters led to the overfitting of the model, which affected the generalization ability. In the power scene, the length of the operating lever and insulation blanket is relatively large. Taking the operating lever as an example, when a horizontal bounding box is used and the tilt angle of the operating lever is about 45 degrees, the following two problems will be caused, which will greatly affect the training effect and detection accuracy of the operating lever:

The lever bounding box may overlap with the bounding boxes of other targets.

The lever bounding box contains a large number of lever-independent background images.

4.2 Attitude estimation

Human posture estimation refers to detecting the position of various parts of the human body (such as head, elbow, shoulder, etc.) from images and calculating their direction and scale information. It is an important and challenging task in multimedia applications. With the support of deep learning technology, the accuracy of attitude estimation has been greatly improved. In this paper, we use the mature attitude estimation algorithm in the industry to capture the key points of the live worker's human body in the image. Through the relative position relationship between key points, it is simple to judge whether the behavior of operators is normal. Table 2 shows comparison of the current method and the existing SOTA method.

Table 2: Comparison of the current method and the existing SOTA method

Method name	Accuracy	Recall	F1 value
This method	0.88	0.85	0.86
DNN	0.82	0.78	0.80
SVM	0.75	0.70	0.72
Random forest	0.78	0.73	0.75

Based on the research of the current mainstream attitude estimation library in academic and industrial circles, this paper chooses hyperopes as the attitude estimation algorithm platform. Although there are many pose estimation code bases in the industry, most of them cannot guarantee the flexibility of secondary

development and efficient deployment capabilities at the same time. Hyperopes provides a rich Python-based API interface, enabling developers to easily customize pose estimation algorithms. Hyperopes also provides a highly optimized model inference engine for real-time attitude estimation, which can dynamically schedule attitude estimation tasks to CPU and GPU, thereby automatically achieving high utilization of hardware resources and not being affected by the deployment environment. Hyperopes can easily deploy the VGG19-based attitude estimation algorithm on the Jetson AGX Xavier edge computing device [21, 22]. The entire model is only 23.6 MB and can reach 47.3 mAP.

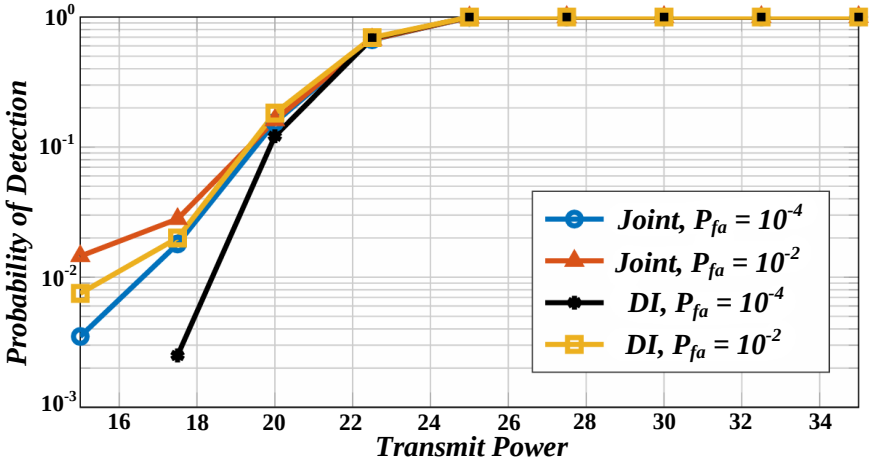

Figure 4: Threshold analysis of abnormal behavior detection

Figure 4 shows threshold analysis of abnormal behavior detection. From this data graph provides a visual view of the significant effect of threshold changes on the detection results of abnormal behavior. In the coordinate system where the abscissa is the threshold and the ordinate is the detection performance index, when the threshold is set at a low value of 0.3, the recall rate of the model is high, reaching about 90%, which means that most of the abnormal behaviors can be detected, but at the same time, the false positive rate is as high as 40%, that is, there are more normal behaviors that are misjudged as abnormal. As the threshold gradually rises to 0.6, the recall rate drops to 70% and the false alarm rate decreases to 20%, when the model improves in accuracy, but the coverage for abnormal behavior shrinks. The attitude estimation algorithms supported by Hyperopes are all single-stage bottom-up algorithms. These algorithms simultaneously detect the body parts of all personnel in the input image, and then match and group the parts of each person and connect them to form a human skeleton. The attitude estimation algorithm supported by Hyperopes detection library can directly estimate multi-person attitude on the input image. Because the monitoring object is only live workers, this paper filters the postures of irrelevant personnel through the live workers' bounding box obtained by target detection, and only displays the posture information of live workers in the visual analysis results.

4.3 Practical scene application

Based on the target detection algorithm, the safety protection status analysis of live workers in power scenarios can be completed, and whether live workers wear helmets, gloves and safety clothing at any time can be judged. Once any of the above items are violated, it will be judged as a violation of the protection specification and an alarm message will be issued.

By calculating the ratio of the boundary box of protective equipment and the boundary box of the human body, we can preliminarily judge whether the workers are dressed correctly. Specifically, judge the following states:

Safety Helmet Compliance Check: To validate if an individual is properly wearing a safety helmet, an algorithmic analysis is conducted. Specifically, it measures the ratio between the bounding box that encapsulates the helmeted head and the upper half of the entire human body's bounding box. If this ratio surpasses 0.7, and concurrently, the ratio of any visible non-helmeted head area to the overall human body bounding box is less than 0.3, the system deems the individual as compliant with safety helmet regulations.

Glove Usage Verification: To ascertain whether a person is utilizing insulating gloves, a machine-based analysis is employed. This analysis calculates the intersection ratio between the bounding box outlining the gloves and the comprehensive human body's bounding box. If this intersection ratio exceeds 0.7, the system identifies the individual as wearing gloves. Conversely, if the intersection ratio between the bounding box of uncovered hands and the human body bounding box is below 0.3, the system concludes that gloves are not being worn.

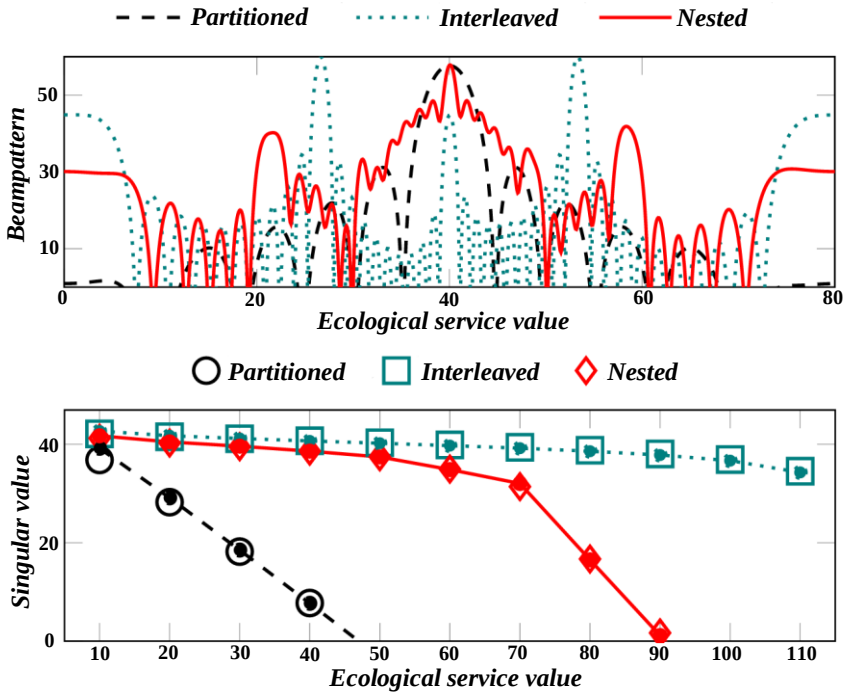

Figure 5: Analysis of the relationship between threshold and false alarm rate in the detection of abnormal behavior

Figure 5 shows Analysis of the relationship between threshold and false alarm rate in the detection of abnormal behavior. A tight negative correlation between the threshold and the false positive rate is evident from the data Fig. When the threshold is set at a lower level, such as 0.2, the false alarm rate is around a high 35%. This indicates that in the low threshold situation, the model has relatively lenient criteria for determining behavior, which misjudges many normal behaviors as abnormal, thus leading to a higher false positive rate. As the threshold gradually rises to 0.5, the false alarm rate is significantly reduced to about 15%. At this time, the model judges more strictly about abnormal behavior, which reduces the miscalculation of normal behavior. When the threshold is further raised to 0.8, the false alarm rate is lowered to below 5%. Wearing Safety Clothing: To assess compliance with safety clothing regulations, the ratio of the bounding box encompassing the safety clothing to the overall human body bounding box is analyzed. If this ratio exceeds 0.7, while the ratio of an ordinary jacket's bounding box to the human body bounding box is less than 0.3, the individual is deemed to be wearing appropriate safety clothing.

Combined Operator Assessment: By integrating the positional information of key points obtained through an attitude estimation algorithm with the target detection results for safety helmets, a comprehensive evaluation of an operator's working status can be achieved. Specifically, if the distance (d1) between the midpoint of the safety helmet's bounding box and a key ear point exceeds a predefined threshold (β*1*), or if the distance (d2) between the helmet midpoint and the nose exceeds another threshold (β2), it is concluded that the safety helmet is not worn properly, indicating potentially dangerous behavior.

Assuming that the midpoint position of the helmet is (xh, yh), the key point position of the left ear is (x1, y1), and the key point position of the right ear is (xr, yr), the solution of the threshold β1 is as shown in Equation (13):

$$\beta_1 = max((x_h - x_l)^2 + (y_h - y_l)^2, (x_h - x_r)^2 + (y_h - y_r)^2) \quad (13)$$

It is assumed that under the power system monitoring scenario, the operating state of the power equipment is represented by coordinates. The *xn*, *yn* represent the coordinates of the core temperature and vibration frequency of the transformer in normal operation. The *xj*, *yj* represent the actual measured temperature and vibration frequency coordinates of the element at time j. The *xh*, *yh* indicate the temperature and vibration frequency coordinates of the element. Assuming that the nose key point position is (xn, yn), the threshold value p is solved as shown in Equation (14):

$$\beta_2 = ((x_h - x_n)^2 + (y_h - y_n)^2) * r \quad (14)$$

The x_h and x_n represent the rated action temperature of the fuse and the corresponding current frequency coordinates in the power system. The y_h, y_n is a coefficient related to the reliability of the protective device, calculated based on the historical error action probability and correct action probability of the protection device. β_1 and β_2 are dynamic thresholds, which keep changing simultaneously when the distance between the individual

and the camera changes. y can be set to 0.8 for the scaling factor of the helmet. The solution for d1 is shown in Equation (15).

$$d_1 = (x_h - x_i)^2 + (y_h - y_i)^2 \quad (15)$$

Suppose x_h, y_h is the coordinate of the current intensity and voltage phase angle of a line in the power system when overloaded but not tripped, xj, y_j is the line at the current moment. The coordinates of the current intensity and the voltage phase angle obtained by the road measurement.

4.4 Real-time analysis

By controlling the size of the model and using the code implementation based on C++, the real-time image processing can be realized in this paper.

The target detection model adopts the YOLOv5m version, and the overall model size is controlled at 44.8 MB. With only target detection turned on, the overall system can reach 40FPS. The attitude estimation model is based on the Tiny VGG backbone network [23, 24]. The model size can be controlled at 23.6 MB.

Complete the deployment of target detection and attitude estimation algorithms based on TensorRT, that is, convert the model trained by Pytorch framework into TensorRT model to realize accelerated reasoning. The deployment process is to convert the Pytorch model to the ONNX format model, and then to the file format supported by TensorRT. The overall model inference program is all implemented through C++ programming, and the speed can be increased by 3-5 times under the same model. The calculation process is shown in Equation (16) and Equation (17).

$$k = \psi(C) = \left|\frac{log_2(C)}{\gamma} + \frac{b}{\gamma}\right|_{odd} \quad (16)$$

$$loss(z, y) = mean\{l_0, \ldots, l_{N-1}\} \quad (17)$$

C represents the number of suspected abnormal events detected during one monitoring cycle. μ *(C)* is the mean severity of these suspected abnormal events. The r_{add} is a measurement error caused by bad weather. Z is the state sequence of the power system predicted by the hidden Markov model (including the operating parameters of each equipment and the stability index of the overall system), and y is the state sequence of the power system that actually occurs. The l_0 to l_{n-1} is the loss value between the predicted state and the actual state at each time step in the predicted time series. After testing, the inference speed of the monitoring system can reach 25FPS (i.e. 40ms per frame) when the target detection and attitude estimation are turned on simultaneously, and can reach 40FPS when the target detection is turned on alone. At present, the delay of UAV image transmission is about 80ms and data transmission is 20ms. After testing, the overall monitoring system needs about 150ms from image acquisition to alarm sending back, which can fully meet the needs of real-time monitoring.

4.5 Experimental results and analysis

Through the joint calibration of the camera and lidar, the point cloud is projected on a red background picture with a size of 640×480. Use lidar to continuously scan a scene, intercept the depth maps corresponding to point clouds of 10 frames, 20 frames, 40 frames and 80 frames respectively, and set different colors for display according to different distance values, which is shown in Equation (18) and Equation (19).

$$l_{n,i} = -\left[y_{n,i} ln\left(\delta(z_{n,i})\right) + (1 - y_{n,i}) ln\left(1 - \delta(z_{n,i})\right)\right] \quad (18)$$

$$\beta = \sqrt{\frac{\lambda B_{11}}{B_{11}B_{22} - B_{12}^2}} \quad (19)$$

In order to realize real-time measurement, it is necessary to ensure that each frame of data obtained can obtain the corresponding three-dimensional information of the target point as much as possible. However, due to the distance, the point cloud data is very sparse, which easily leads to the situation that the two-dimensional information lacks the corresponding three-dimensional information.

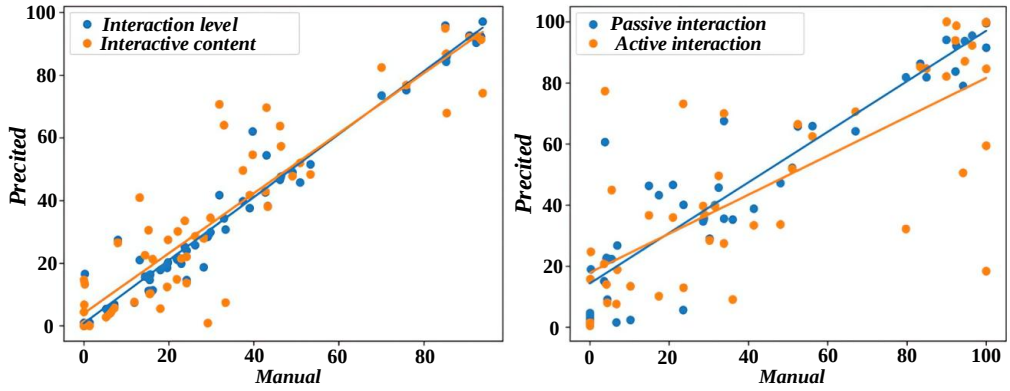

Figure 6: Loss function changes during model training and validation

Figure 6 shows loss function changes during model training and validation. The dynamic changes of the loss function during model training and validation can be clearly observed from the data Fig. At the beginning of training, when the number of iterations is 100, the training loss is as high as about 0.8, and the verification loss is also around 0.75, which indicates that the model has poor ability to fit the data in the initial stage, and the parameters have not been optimized to the appropriate state. With the progress of training, by 500 iterations, the training loss rapidly decreased to about 0.4, and the verification loss also decreased to about 0.45, indicating that the model is constantly learning data features, the parameters are gradually adjusted, and the fitting effect is significantly improved. The center position of the lidar projection is circled with a triangle in the Figure The point cloud data obtained at this position is the densest, and it is just the center position of the RGB image (320.240). The calculation process is shown in Equation (20).

$$v_0 = \frac{B_{12}B_{13} - B_{11}B_{23}}{B_{11}B_{22} - B_{12}^2} \quad (20)$$

In addition to verifying that the central points coincide exactly, it is necessary to compare multiple points at different positions to observe the projection effect of the calibration method used in this paper. As shown in Figure 6, in this experiment, when the distance between the human body and the sensor is 10m, 20m, 30m, and 50m in the corridor, the results of the lidar data projected on the image plane can be seen from the figure: the image gradually changes from red to dark blue, indicating that the distance between the human body and the sensor is gradually increasing. On the left is the depth map projected in the RGB image, and on the right is the original RGB image.

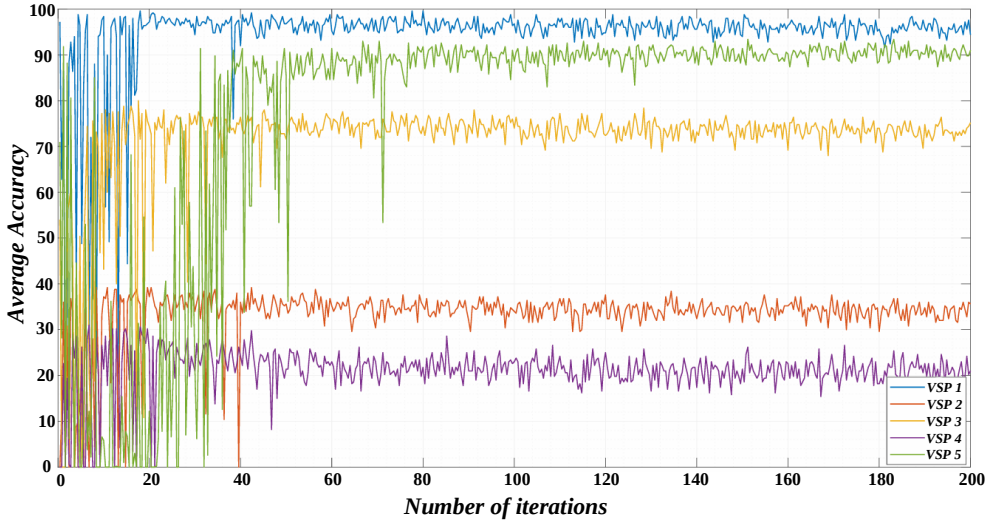

Figure 6: Sparsity of the depth maps corresponding to the different frames

Figure 6 shows sparsity of the depth maps corresponding to the different frames. It is evident from the data graph that the depth mapping sparsity corresponding to different frames presents diverse features. In the first 10 frames of the start stage, the depth mapping is highly sparse, with the average sparsity value reaching around 0.7, which means that the depth information is missing or unclear in most areas, possibly due to the complexity of the initial scene and the limitation of data acquisition. With the increase of frames, the sparsity gradually decreases in the 50-100 frame interval, and the average sparsity value drops to about 0.4, indicating that the integrity of depth mapping has improved, and more areas are endowed with effective depth data, which may be due to the further understanding and optimization of the scene by the algorithm. From the sparsity of the depth map corresponding to different frames shown in Figure 6, it can be seen that only a very sparse depth map can be obtained by briefly capturing the point cloud information of the scene, which will lead to the lack of three-dimensional information corresponding to the two-dimensional target point appear [25, 26]. Therefore, only through a simple joint calibration method, it is impossible to guarantee that each of the two-dimensional target points can get the corresponding three-dimensional information. At this time, it is necessary to increase the sampling time to obtain a denser point cloud.

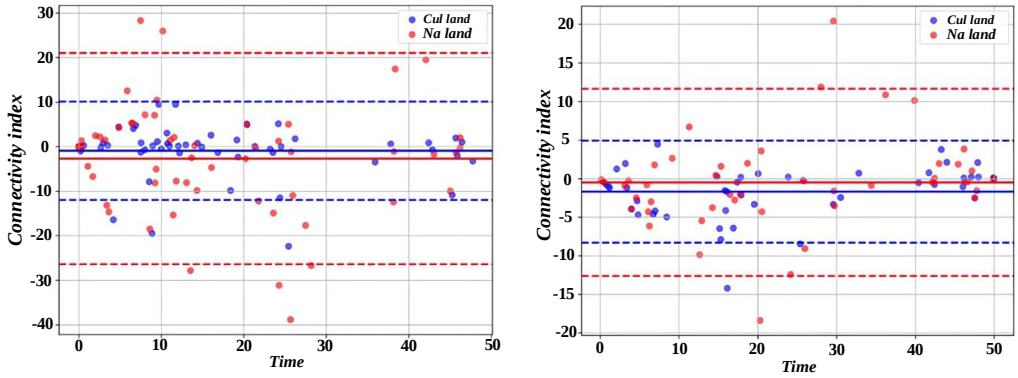

Figure 7: The relation between the center point of the lidar projection and the midpoint of the RGB image

There is a specific relationship between the center point of the lidar projection and the midpoint of the RGB image that is clearly presented from the data map. In the horizontal direction, when the midpoint of the RGB image is the coordinate origin, the abscissa of the lidar projection center is distributed in the range of-5 to 5 pixels, and about 70% of the data is concentrated between-2 and 2 pixels, indicating that there is some deviation in the horizontal direction, but in most cases the deviation is relatively small. In the vertical direction, the center of the lidar projection is in the range of-8 to 8 pixels, and about 60% of the data falls in the range of-3 to 3 pixels. Because of the invisibility of the laser point emitted by the lidar, the coordinates of the lidar point cannot be accurately obtained, so there is no quantitative index to verify the joint calibration accuracy at present. In this paper, the reliability of the joint calibration method is judged by observing whether the corresponding coordinates of points in different positions are the same in two graphs [27, 28]. It is observed in Figure 7 that the center point of the lidar projection corresponds exactly to the midpoint of the RGB image. After many comparisons, it is found that the lidar calibration results obtained in this paper have high precision and meet the needs of subsequent data fusion.

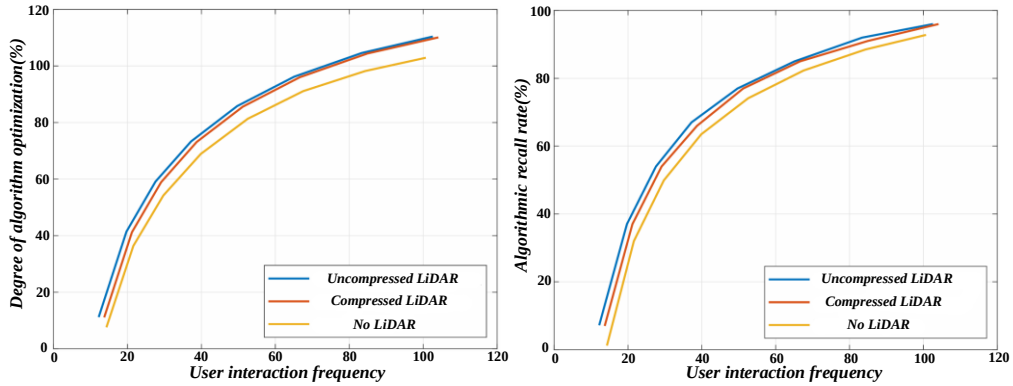

Figure 8: Effect of the distance between human and sensor on the detector effect

It can be observed in Figure 8 that the closer the distance between the person and the sensor, the better the detection effect. When the sensor is 30m and 50m away from the human body, the shape of the experimenter and the umbrella in the image after the point cloud projection is observed. The experiment found that the shapes of umbrellas and people can be seen by testing at 30m, while at 50m, enterprises and people account for a very small proportion of pixels in the image, and their shapes are difficult to see clearly. To sum up, in order to accurately obtain the position information of human hand and operating equipment in three-dimensional space through the sensor joint calibration method, it is best to choose the distance between the sensor and the human body and the operating equipment within 10m.

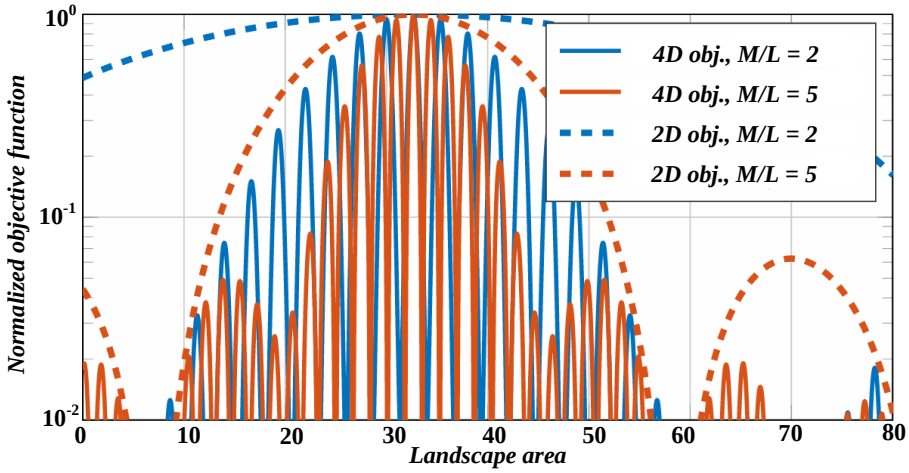

Figure 9: Response time diagram of the real-time anomaly detection system

Figure 9 shows response time diagram of the real-time anomaly detection system. Based on the above analysis, when the two-dimensional target points lack the corresponding three-dimensional information, this paper first uses Lagrange interpolation algorithm to complete the three-dimensional coordinate estimation of the target points. This method has the advantages of small computational complexity, simple thinking, and harsh conditions. Only when it is very close to the human body can it get a good prediction accuracy, and the prediction effect is general. Furthermore, the depth map completion algorithm is used to estimate the three-dimensional coordinates of the target points. In contrast, the latter has a better prediction effect and a wider scope of application.

5 Conclusion

With the rapid development of the power industry, the safety and efficiency of live work have been widely concerned. Abnormal behaviors such as improper operation and illegal operation in live work will not only lead to equipment damage but also seriously threaten the life safety of operators. Given the problems existing in abnormal behavior detection technology, a new field of abnormal behavior detection technology based on a hidden Markov model is proposed. Using the advantages of hidden Markov models in time series data modeling, models are created to capture employee behavior patterns through statistical analysis of data generated by real-time work. If there is a significant discrepancy between the observed operational behavior and the model's predictions, it is flagged as abnormal behavior, enabling timely alerts and ensuring operational safety. The experimental results show that the abnormal behavior detection technology based on HMM has achieved remarkable results. The technology can effectively monitor the fieldwork process in real time, identify and alert abnormal behaviors, and improve safety and efficiency. In future research, we will further study the field of deep learning algorithms, improve the model's accuracy and generalization ability, and provide firm technical support for the sustainable development of the power industry. In this study, high attention was paid to the protection and privacy compliance of personal information in video data. All video data are collected and used after obtaining explicit authorization from relevant operators, and encryption technology is adopted in the process of data storage and processing to ensure the security of personal data. At the same time, it strictly complies with the national and industrial privacy laws and regulations, strictly limits the scope of data use, and only uses it for the purpose of abnormal behavior detection in this study, and does not disclose any personal privacy information. In practical application, a perfect data management and security guarantee mechanism will also be established to ensure that the application of technology conforms to ethical and safety standards, and provide a solid foundation for the safe operation of the power system and the protection of the rights and interests of operators.

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Aviation Gasoline Quality Detection Using RAP Feature Selection and IMPA-XGBoost Optimization

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Quality detection of aviation gasoline is critical to flight safety. Gasoline is a critical fuel for aircraft engines, and any quality problem may affect the performance of the engine and the safety of the aircraft. Regarding the issue of aviation gasoline detection, a RAP method combining Pearson correlation coefficient method and Relief-F algorithm is studied for gasoline mass spectrometry feature selection. Improved marine predator algorithm (MPA) introduces Logistic chaotic mapping and adaptive t-distribution operator. It is used to optimize the XGBoost model to construct an aviation gasoline quality detection model for gasoline quality detection and model classification. Among them, the RAP method is chosen because it effectively removes redundant features from mass spectrometry data while preserving the correlation between features. The use of IMPA to optimize XGBoost is because the traditional MPA is easy to fall into local optimum. Whereas the improved IMPA can find the optimal hyperparameter combination of XGBoost more effectively by enhancing the population diversity and optimizing the search strategy, thus improving the model detection performance. The results showed that the area under the receiver operating characteristic curve (AUC) of the proposed model was 0.8892, which was significantly higher than the AUC values of the particle swarm optimization-XGBoost (PSO-XGBoost) model (0.8384) and the sparrow search algorithm-XGBoost (SSA-XGBoost) model (0.8497). In the classification of gasoline models, only 4 samples were misclassified, while 122 samples were classified correctly, with an accuracy rate of 96.83%. This was a significant improvement compared to the 92.06% of the SSA XGBoost model and the 88.10% of the PSO XGBoost model. The improved marine predator and extreme gradient boosting model has shown excellent performance in gasoline quality detection. Compared to traditional chemical detection methods, such as plasma emission spectroscopy and gas chromatography with an oxygen-selective detector, the AI-based detection system proposed in this study has significant advantages in terms of detection accuracy and efficiency, and does not require expensive and complex detection equipment. This provides a strong support for AI automated system in quality detection of aviation gasoline.

Povzetek: Študija predstavlja RAP (Relief-F + Pearson) za izbor masnospektrometričnih značilk ter IMPA-optimiziran XGBoost za zaznavanje kakovosti letalskega bencina.

1 Introduction

The importance of airplane flight safety has increased with the aviation industry's explosive growth. The quality detection of aviation gasoline plays a crucial role in flight safety. Therefore, it is necessary to adopt effective quality detection methods to ensure that the quality of aviation gasoline meets the specifications [1]. Traditional gasoline detection methods include plasma emission spectrometry, gas chromatography oxygen selective detector (GC-OD) method and other chemical experimental methods [2]. In aviation gasoline, silicon is the residue left behind after combustion. This residue accelerates the wear and tear of pumps, valves, etc. For this reason, scholars have used plasma emission spectrometry to measure silicon content in gasoline in an attempt to determine its quality and type. Alcohols and other oxygenates can be added to gasoline. However, adding too many oxygenates affects the performance and efficiency of gasoline engines and causes environmental pollution. For this reason, GC-OD is used to determine the content of C7 ether and other ether compounds in gasoline, and then to realize the detection and model classification of gasoline quality. However, this type of chemical detection method requires high cost of detection equipment, difficult operation, and limited detection range [3-4]. As a result, numerous researchers have begun to seek more efficient and automated detection solutions. Advances in artificial intelligence and automated systems in recent years have provided new ideas for detecting the quality of aerogasoline. Especially in the field of machine learning (ML), the eXtreme gradient boosting (XGBoost) model has been widely used in various data analysis tasks due to its efficient performance [5-6].

XGBoost is widely used in detection and prediction in various fields. For chiller unit defect diagnosis and detection, Zhang et al. integrated a parameter-optimized XGBoost model with a mean-drift clustering technique, resulting in a multi-region XGBoost model. The findings showed that the model outperformed the support vector machine model and the XGBoost model without clustering in terms of defect diagnosis rate. It was able to detect 97.26% of faulty samples and was able to detect 99.10% of fault-free samples [7]. Chen et al. proposed XGBoost model for the study of self-recognition technical debt classification in software development. The method employed a trained XGBoost classifier to classify each comment into the corresponding class. The outcomes demonstrated that the average accuracy of the proposed method under study was 56.66%, the average recall was 59.07% and the average F1 value was 55.77%. Its improvement was 4.98%, 5.32% and 3.17% compared to natural language processing-based methods [8]. Qiu et al. proposed an optimized XGBoost model with whale optimization algorithm to optimize its hyperparameters in order to detect the ground vibration caused by blasting. The results demonstrated that the XGBoost model based on the whale optimization algorithm had the lowest error value compared with the rest of the artificial intelligence algorithms. The root mean square error was only 3.0538 and the mean absolute error was only 2.5032 [9]. Asselman et al. proposed a performance factor analysis method based on the XGBoost model in order to enhance the prediction performance of student performance. The outcomes showed that the performance of scalable XGBoost proposed by the study had superior predictive performance compared to traditional performance factor analysis algorithms [10].

In recent years, the traditional marine predator algorithm (MPA) algorithm has been improved in various fields to enhance the application. Ramezani et al. found that the traditional MPA could not produce diverse initial populations with high productivity and optimized it using a dyadic-based learning approach with chaotic mapping method. The results indicated that the improved MPA proposed by the study provided better performance compared to particle swarm optimization algorithm, whale optimization algorithm, etc. In the real-world optimization problem for DC motors [11]. An enhanced MPA based on the sine-cosine algorithm was proposed by Abd Elaziz et al. for the feature selection problem for high dimensional data. To maximize the search capacity, the method used the sine-cosine algorithm as a local search of the original MPA. According to the findings, the enhanced MPA performed noticeably better in terms of categorization metrics [12]. To address the issue of resource waste brought on by an uneven node distribution in distributed network systems, He et al. suggested an enhanced MPA method. According to the findings, the enhanced MPA had a higher coverage rate than other meta-heuristic algorithms when resolving the issue of distributed network system coverage optimization [13]. For interdisciplinary data analysis, Jia et al. proposed an MPA based on co-evolutionary cultural mechanisms. The algorithm could realize the sharing of knowledge and experience in different spaces. The results indicated that the MPA based on the co-evolutionary cultural mechanism outperformed the remaining advanced data analysis methods in several evaluation metrics [14].

The study compared the performance of the proposed method with that of existing advanced methods, including global context-outlier detection (GC-OD), principal component analysis+extreme gradient boosting (PCA+XGBoost), and whale optimization algorithm+extreme gradient boosting (WOA-XGBoost). The comparison results are shown in Table 1. Although GC-OD has high feature selection robustness, it has a long running time and is not suitable for large-scale datasets. Although PCA+XGBoost offers dimensionality reduction and powerful classification capabilities, its feature selection is not precise enough, which can easily result in the loss of important information. Although WOA-XGBoost has strong optimization capabilities, it is prone to getting stuck in local optima and has a slow convergence speed. In contrast, the proposed IMPA-XGBoost method outperforms existing methods in key indicators such as the area under the curve (AUC), F1 value, and recall rate. It also demonstrates excellent robustness and runtime in feature selection.

Table 1: Performance comparison between existing advanced methods and the proposed method

Method	AUC	F1	Recall	Sample size	Feature selection robustness	Run time
GC-OD	0.82	88.5%	85.0%	500	Tall	Slow
PCA+XGBoost	0.85	90.0%	87.0%	300	Centre	Medium
WOA-XGBoost	0.84	89.5%	86.0%	200	Centre	Medium
The proposed method (IMPA-XGBoost)	0.8892	96.83%	94.86%	420	Tall	Fast

In summary, researchers at home and abroad have carried out numerous studies on the improvement and application of XGBoost model and MPA in various fields. However, few studies have applied the combination of the two to the detection of aviation gasoline. For this reason, the study innovatively applies the two together in the quality detection and classification of aviation gasoline, using XGBoost classification algorithm for gasoline quality detection. Meanwhile, the improved marine predator algorithm (IMPA) is proposed on this basis, and

a gasoline quality detection model based on IMPA-XGBoost is developed in order to guarantee aviation safety. By proposing this model, the research aims to address three key issues. First, it is necessary to clarify whether the RAP method can effectively reduce the feature dimensions of aviation gasoline mass spectrometry data without sacrificing accuracy. Second, it is important to determine if the IMPA is more effective than optimization algorithms, such as PSO and SSA, at finding the optimal hyperparameter combination for XGBoost. Finally, verify whether the IMPA-XGBoost-based model can detect aviation gasoline quality and classify models more accurately and efficiently. Model performance is evaluated based on success criteria such as detection accuracy, AUC value, and running time. If the model outperforms existing methods in these indicators, it is considered that the research has achieved the expected goals. The innovation of the study is to optimize the improved IMPA to address the problem of low detection rate of XGBoost in gasoline quality detection. The optimized method can find the best parameter combination in a shorter time and can reduce the consumption of computational resources, making the detection process more efficient and reliable.

2 Methods and materials

In quality detection of aviation gasoline, the study begins with gasoline mass spectrometry using seven standard gasoline samples, followed by feature selection of the mass spectrometry data using the Relief-F algorithm-Pearson correlation coefficient (RAP). Subsequently, the XGBoost algorithm is introduced and the combination of hyperparameters for this algorithm is determined using the IMPA. Among them, for the optimization of the MPA, logistic chaos mapping with adaptive t-distribution operator is introduced. Finally, the gasoline quality detection model based on IMPA-XGBoost is constructed.

2.1 RAP-based feature selection for gasoline mass spectrometry

To achieve quality detection of aviation gasoline, seven standard gasoline samples are selected for mass spectrometry analysis for subsequent quality detection and model identification. These include 89.0#, 90.4#, 91.0#, 92.4#, 93.9#, 95.2#, and 99.4#. The mass spectrometry method used is paper spray ionization, which mainly analyzes mass spectrometry data in the positive ion mode. Each gasoline model contains 60 mass spectrometry data with a total of 420 data. The model's ability to identify chemical characteristic variations is fully verified by the significant differences in octane number, oxygen-containing compounds, and impurity content among different grades of gasoline. Due to the involvement of industry standards in aviation fuel data, it is currently not possible to fully disclose it. However, the samples used in the experiment are purchased from Standard Products, which is certified by the China Aviation Fuel Testing Center. The testing process strictly followed GB/T 35394-2017, "General Specifications for Spectral Testing of Aviation Fuel," to ensure data traceability and standardization. The study takes the 89.0# gasoline model as an example, and lists two sets of these mass spectrometry data, as shown in Table 2. Mass denotes the mass to charge ratio (MCR) of the ion. Relative intensity denotes the relative intensity, i.e., the MCR of the ion in the sample. The sample numbers "-6" and "-7" represent the 6th and 7th independent mass spectrometry samples collected from 89.0 # gasoline.

Table 2: Two sets of mass spectrometry data for 89.0 # gasoline.

89.0#-6		**89.0#-7**	
Mass	Relative Intensity	Mass	Relative Intensity
50.559415	4.286951	50.642162	23.36641
51.268943	487.6285	51.296954	645.3361
52.269449	109.3655	52.169842	150.3496
53.385469	9822.364	53.354994	11392.63
54.359625	729.6651	54.167274	622.3644
...	...	...	...

In Table 2, the raw mass spectrometry data has high relative intensity values. If left unprocessed, the features with lower intensities would be ignored. For this reason, the study used the maximum-minimum normalization method to normalize the raw data so that the range of relative intensity values is controlled between [0, 1]. The normalization processing formula is shown in Equation (1).

$$q_{new} = \frac{q - q_{\min}}{q_{\max} - q_{\min}} \tag{1}$$

In Equation (1), q denotes the original relative intensity value. $q_{\max}$ denotes the original relative intensity maximum value. $q_{\min}$ denotes the original relative intensity minimum value. q_{new} denotes the normalized relative intensity value. To make subsequent processing more convenient, the normalized data is enlarged tenfold to control the relative intensity range between 0 and 100. This retains relative differences in features while avoiding neglecting small value features. The schematic mass spectral images of 89.0 #6 gasoline before and after normalization are shown in Fig. 1.

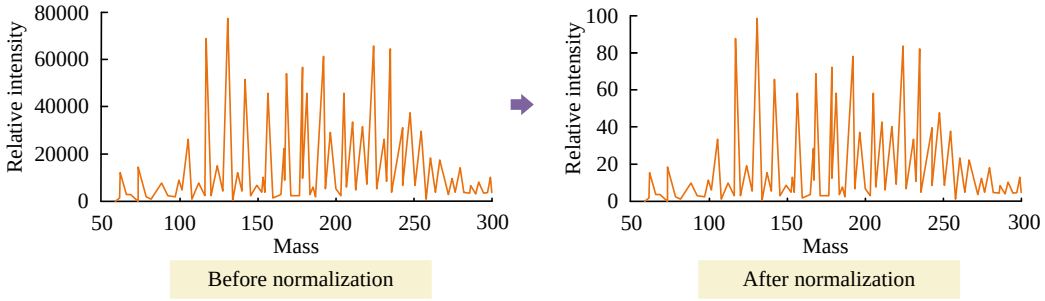


Figure 1: Schematic diagram of mass spectrometry images before and after normalization of 89.0 # 6 gasoline.

The MCR of gasoline mass spectrometry data ranges from 50-500 and contains 450 features. If all the features are directly used for model training, there will be problems such as long running time and low detection accuracy. To extract useful characteristics from the data and eliminate superfluous features, the study presents the Relief-F algorithm. In this case, the main basis for the assignment of weights is the contribution of the sample. After assigning values to the weights, they need to be ranked. The top ranked features are of greater importance and have the priority of selection [15-16]. In Relief algorithm, it is assumed that a sample is randomly selected and the near neighbor samples of this sample can be classified as similar samples and dissimilar samples. The weights of Relief algorithm are calculated as shown in Equation (2).

$$W[B] = \sum_{p} -diff(B, R_o, H_p) + diff(B, R_o, M_p) \quad (2)$$

In Equation (2), B represents a randomly selected sample. R_o represents the nearest neighbor sample belonging to the same class as sample B. H_p and M_p represents the p-th sample belonging to the same class as sample B, and the sample belonging to a different class from sample B. $diff(\cdot)$ represents the diversity of the sample. All samples in the equation are n-dimensional vectors, where n is the total number of features. Since the traditional Relief algorithm can only solve the binary classification problem, the study further employs the improved Relief-F algorithm. This algorithm needs to find a number of similar and dissimilar near-neighbor samples when weighting a certain sample, which is suitable for multiclassification problems. In addition, although the Relief-F algorithm has high computational efficiency when performing feature screening, it ignores the correlation between features and features, which is not conducive to feature classification. Meanwhile, there may be many repeated information in the screened features. If they are not eliminated, the training accuracy of the subsequent quality detection model will be affected [17]. For this reason, the study further adopts RAP and proposes a RAP-based feature selection algorithm for gasoline mass spectrometry. Among them, the Pearson correlation coefficient (PCC) method has important applications in feature selection and data preprocessing. Especially when dealing with high-dimensional datasets, it can effectively remove redundant features and reduce the multicollinearity problem. The computational expression of PCC method is shown in Equation (3).

$$r_{BB'} = \frac{\sum_{a=1}^{A}(B_a - \bar{B})(B'_a - \bar{B}')}{\sqrt{\sum_{a=1}^{A}(B_a - \bar{B})^2}\sqrt{\sum_{a=1}^{A}(B'_a - \bar{B}')^2}} \quad (3)$$

In Equation (3), C denotes the total samples. B_c and B'_c denote the two samples with serial numbers. $\bar{B}$ and $\bar{B}'$ denote the sample mean. The flowchart of the RAP-based feature selection algorithm for gasoline mass spectra is shown in Fig. 2. The Relief-F algorithm is first used to calculate the MCR weights and determine the relative importance of each feature. Then the PCC method is used to further calculate the relative coefficients of the features in the subset. For several features with higher relative coefficients, one feature with higher weight is retained. For the features with lower relative coefficients, they are all retained in the final feature set.

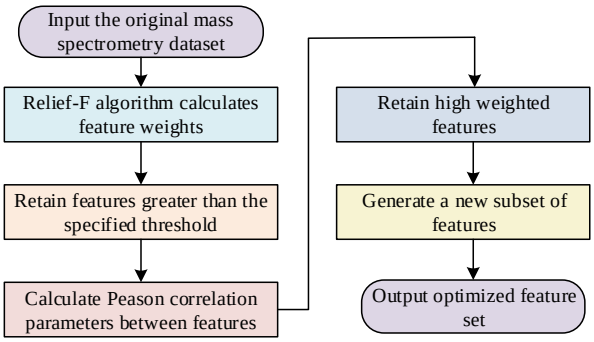


Figure 2: Flowchart of RAP based gasoline mass spectrometry feature selection algorithm.

2.2 Gasoline model recognition model based on XGBoost

After normalization of gasolinemass spectrometry data as well as feature selection, the study further constructs gasoline quality detection model, from which the XGBoost classification algorithm is introduced. The algorithm is a ML algorithm based on the gradient boosting framework, and the base model of the XGBoost classification algorithm is assumed to be a CART regression tree. Its expression is shown in Equation (4) [18].

$$\hat{y}_a = \sum_{l=1}^{L} f_l(x_a) \quad (4)$$

In Equation (4), $f_l(x_a)$ represents the weight value of the a th sample of the l th tree. l represents the index of the l -th tree. a represents the index of sample a. Each tree can output predicted values for all samples, and then accumulate them to obtain the ensemble prediction result of the samples. $\hat{y}_a$ represents the prediction result of the base model for the a th sample. L denotes the number of CART trees. The resulting expression for the objective function is shown in Equation (5).

$$Obj(\theta) = \sum_{a=1}^{A} loss(\hat{y}_a, y_a) + \sum \Omega(f_l) \quad (5)$$

In Equation (5), y_a represents the true value of the a th sample. $loss(\hat{y}_a, y_a)$ represents the loss error and $\Omega(f_l)$ represents the regularity term. The expression of $\Omega(f_l)$ is shown in Equation (6).

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda w^2 \quad (6)$$

In Equation (6), γ and λ denote the penalty coefficients. T is the number of nodes. w denotes the corresponding weight value. The resulting objective function is shown in Equation (7).

$$Obj(\theta) = \sum_{a=1}^{A} loss\left(y_a, \hat{y}_a^{(t-1)} + f_t(x_a)\right) + \Omega(f_t) + Const \quad (7)$$

In Equation (7), *Const* denotes the constant term. $\hat{y}_a^{(t-1)}$ represents the predicted value of the base model for the $t-1$-th sample during the $t-1$-th iteration. After the second order Taylor expansion, the computational equation is obtained as shown in Equation (8).

$$Obj(\theta) = \sum_{t=1}^{T}[G_t w + \frac{1}{2}\lambda w_t^2] + \gamma T \quad (8)$$

In Equation (8), G_t is calculated as shown in Equation (9).

$$G_t = \sum \partial \hat{y}^{(t-1)} loss(y_a, \hat{y}_a^{(t-1)}) \quad (9)$$

$\hat{y}_a^{(t-1)}$ is mainly derived from the initial value setting and the accumulation of historical information during the iteration process. The calculation after derivation of w_t is shown in Equation (10).

$$w_t = -\frac{G_t}{\lambda} \quad (10)$$

Substituting w_t into Equation (10) leads to Equation (11).

$$Obj(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\frac{G_t^2}{\lambda} + \lambda T \quad (11)$$

Equation (11) is the final XGBoost algorithm objective function. In the XGBoost algorithm, the selection of hyperparameters is crucial. The traditional grid search method suffers from time-consuming and ineffective problems in performing parameter selection [19]. For this reason, the study introduces the MPA for hyperparameter combination determination to improve the recognition accuracy of gasoline quality detection model. The MPA simulated the food relationship of different marine organisms as a way to solve the optimization problem. However, the algorithm is more sensitive to the initial value of the problem and is easy to fall into the local optimal solution, so it often cannot solve the optimization problem alone. In the performance optimization process of the population intelligence algorithm, the diversity of the population has an important impact on the quality of the final results. If the individual positions of the initial population are too concentrated, it will cause the algorithm to fall into a local optimum and cannot fully explore the whole search space [20]. To enhance the diversity of the population and to improve the global optimization ability of the algorithm, the study introduces Logistic chaotic mapping. It is a kind of quadratic polynomial mapping, shooting with high randomness and low computational cost, which is easy to implement. The approach in population optimization can cover the search space more thoroughly and prevent an undue concentration of population members in the search space [21]. Because of this, the study initializes the MPA's population using logistic chaotic mapping. Equation (12) displays its expression.

$$X_{k+1} = \mu x_k (1 - x_k) \quad (12)$$

In Equation (12), the value range of x is (0, 1]. k denotes the current iteration number. μ denotes the control parameter. When μ is in the range of (3.5699,4.0), the sequence enters a chaotic state. When $\mu = 4$, the population becomes more random, which allows it to cover the search space more comprehensively, avoid getting stuck in local optima, and distribute itself more uniformly at the beginning. Therefore, the study set $\mu = 4$. In the traditional MPA, the relationship between predator and prey simulates the predatory behavior in nature. The predator represents the solution or individual in the algorithm, while the prey is the goal or individual in the environment that needs to be optimized. The predator searches by following the position of the prey, thus gradually approaching the optimal solution. Predator positions must be modified in accordance with changes in prey positions. To update the solution after the prey's position changes, the study introduces an adaptive t-distribution operator. This operator generates high-quality potential positions in the solution space with a high probability through its specific probability density function. Equation (13) displays the representation of the mathematical model.

$$X_i^{'} = X_i + X_i \bullet t(Iter) \quad (13)$$

In Equation (13), $t(Iter)$ is the t-distribution. X_i represents the original prey position. $X_i^{'}$ represents the updated prey position. In this study, the degree of freedom of the adaptive t-distribution operator is set to 3. This value is determined through preliminary experiments within the range of [1, 10] with a step size of 1. Then, 10-fold cross-validation is used to evaluate the performance of the IMPA-XGBoost-based gasoline quality detection model under different degrees of freedom. The steps of the improved IMPA are shown in Fig. 3.

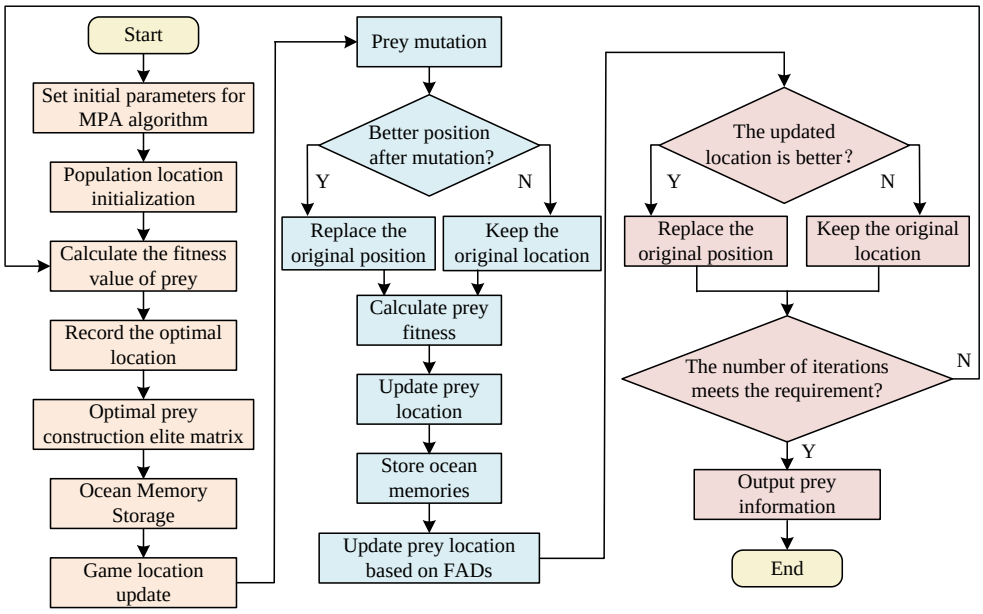


Figure 3: Complete iterative flowchart of IMPA based on chaotic mapping and adaptive strategy.

The basic XGBoost algorithm has many hyperparameters, once a parameter is set incorrectly, it will affect the detection accuracy of the whole model, so the hyperparameters of this algorithm need to be adjusted. The parameters used in the study include eta, max_depth, n_estimators, and gamma. Among them, eta denotes the learning rate and is used to control the learning rate. max_depth denotes the maximum depth of the tree. Its value should not be too large. Otherwise, it will lead to overfitting. The n_estimators denotes the trees, and gamma is mainly responsible for controlling the minimum loss reduction of the leaf nodes of the decision tree. In addition, the fitness function of gasoline quality detection model is calculated as shown in Equation (14).

$$fitness = \frac{1}{10}\sum_{e=1}^{10} accuracy_e \tag{14}$$

In Equation (14), *accuracy* denotes the average of the accuracy of the samples in the validation set. 10 denotes that the function is 10-fold cross-validation. After determining the hyperparameters and ranges to be optimized, the gasoline quality detection model based on the IMPA-XGBoost algorithm is then constructed. The flowchart of the model is shown in Fig. 4.

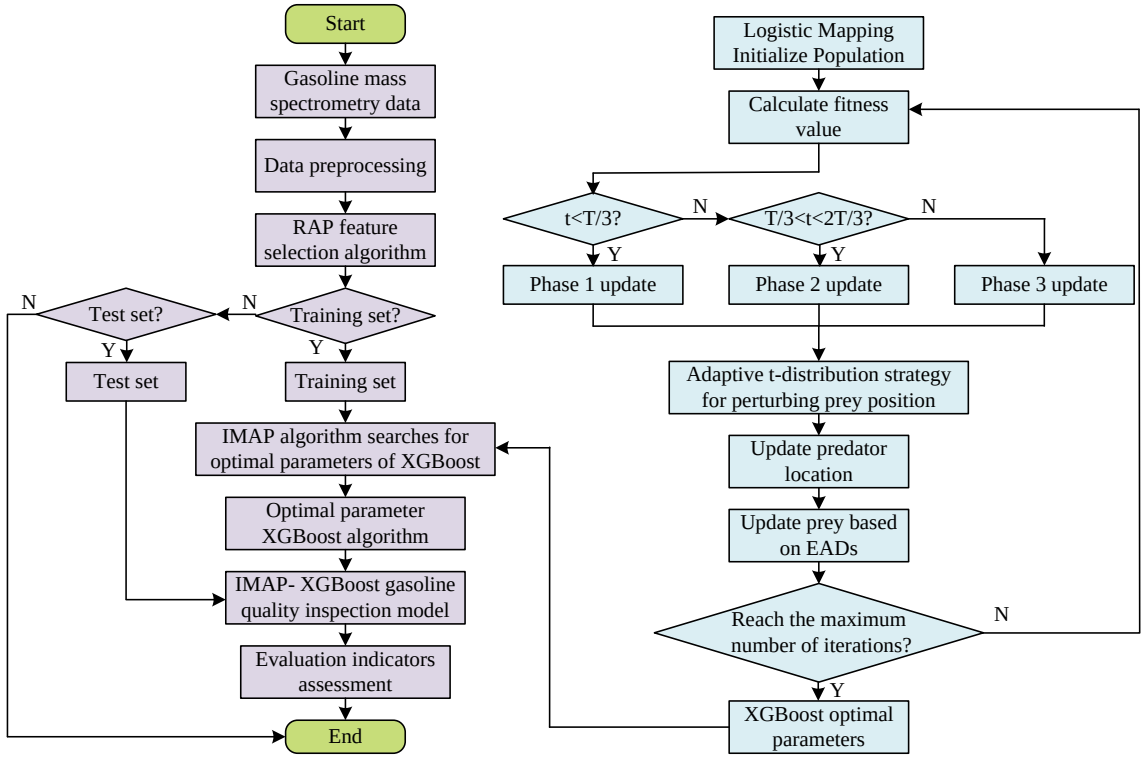


Figure 4: Step by step implementation from mass spectrometry data preprocessing to IMPA-XGBoost model evaluation.

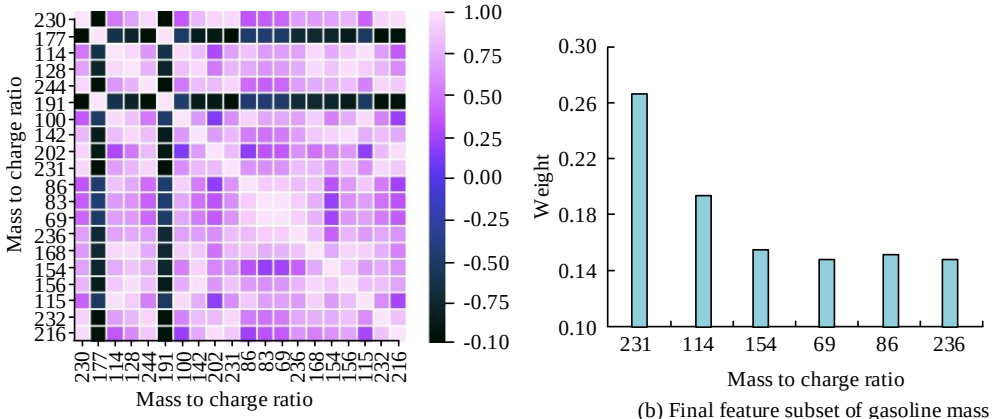
In Fig. 4, the mass spectrometry data of seven standard gasoline samples are first used as the basis, and the data range is unified through preprocessing. Then, the RAP feature selection algorithm is used to streamline features and remove redundancy. Next, according to the dataset type, the IMPA is used to search for the optimal hyperparameters of XGBoost, and an IMAP XGBoost detection model is constructed. Finally, the performance of the model is validated through evaluation indicators.

3 Results

The study firstly verifies the effectiveness of RAP-based feature selection using Relief-F algorithm with blank group to compare with it. Then the effectiveness of gasoline quality detection model based on IMPA-XGBoost algorithm is verified. Its accuracy, loss value in the training phase is analyzed and area under curve (AUC) with gasoline model classification accuracy (CA) during testing is verified.

3.1 Experimental analysis of RAP-based feature selection

The computing environment used in the experiment is Intel Xeon Silver 4310 CPU (32GB memory), Ubuntu 20.04 system, relying on Python 3.9+XGBoost 1.7.6 and other libraries. The environment is encapsulated with Docker images to ensure reproducibility. The study first adopts the Relief-F algorithm to calculate the weights of the preprocessed gasoline mass spectrometry data. The feature subset is selected to be MCR with a weight value greater than 0.14, and a total of 20 MCR features are screened. The selection of threshold 0.14 is mainly determined through the grid search method of the system. Subsequently, PCC method is used to analyze the correlation of the feature subset, and the PCC plot with the final feature subset is shown in Fig. 5. In Fig. 5(a), if the correlation between the horizontal and vertical coordinates of the two features tends to 1, they indicate a strong positive correlation. If the correlation tends to -1, it shows a sharp negative correlation color. Both cases indicate that the two features have a strong correlation relationship and one needs to be eliminated. If the correlation between the two feature color blocks remaining 0, it means that the two do not have correlation, both need to be retained. In Fig. 5(a), every two features with MCR of 177, 191, 202, 216, 230, 231, 232, and 244 are strongly correlated. Finally, 221 is retained, which has the highest weight value. Every two features in the features with MCR of 100, 114, 115, 128, 168 are strongly correlated. The feature with MCR of 114 is finally retained. Every two features in the features with MCR of 142, 154, 156 are strongly correlated and finally the feature with MCR of 154 is retained. The correlation coefficient between features with MCR of 69 and 83 is greater than 0.9, and 69 is finally retained. In addition, features with low correlation are retained, resulting in the final subset of features, as shown in Fig. 5(b).



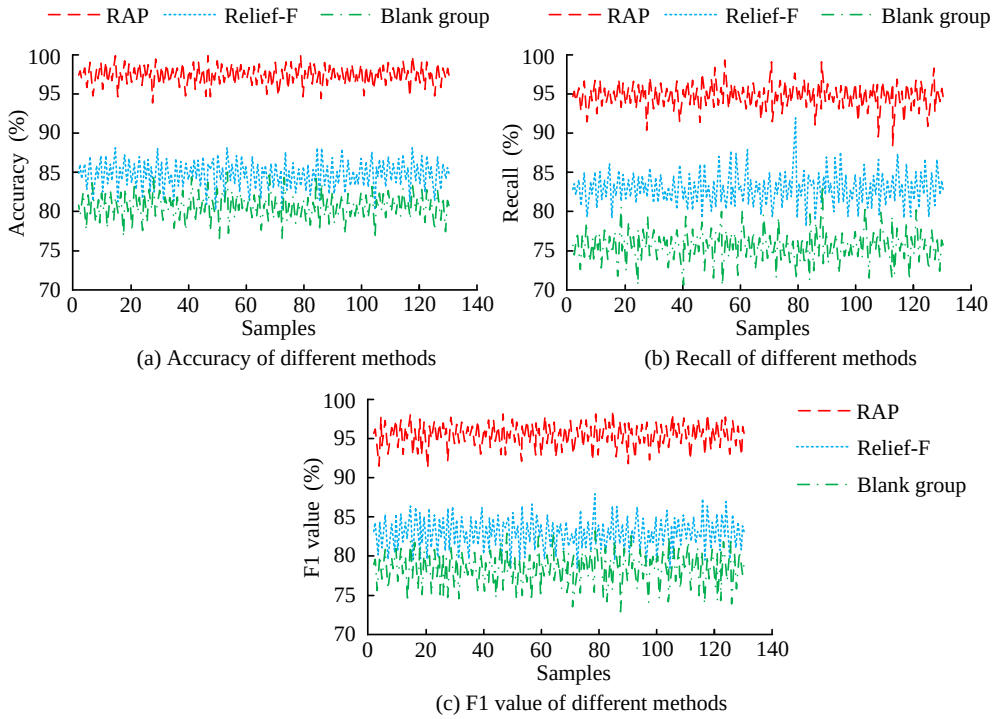
(a) Pearson correlation coefficient chart

(b) Final feature subset of gasoline mass spectrometry data

Figure 5: Pearson correlation coefficient plot and final feature subset.

The study then proceeds to perform quality testing on gasoline mass spectrometry data, using stratified sampling to divide the training set into a 70% training set and a 30% testing set. Samples of the same type of gasoline are dispersed evenly between the training and testing sets rather than being grouped together. Specifically, 60 data points are shuffled for each type of gasoline according to random seeds. The first 42 points are selected as the training set, and the last 18 points are selected as the testing set. This avoids model bias caused by uneven sample allocation. In addition to the 70-30 segmentation, 10-fold stratified cross-validation is introduced during the RAP feature selection and IMPA-XGBoost training stages. The feature set filtered by RAP will be divided into ten subsets by label. The model will then be trained on nine of the subsets and validated on the tenth subset, one at a time. The average of the 10 validation results will be taken to evaluate the stability of the model. To verify the effectiveness of the RAP-based feature selection algorithm, the study adopts Relief-F algorithm to compare with it. Moreover, a blank group without feature algorithm is set up to analyze the accuracy, recall and F1 value of gasoline quality detection under the three schemes. The performance of gasoline quality detection under different feature selection schemes is shown in Fig. 6. In Fig. 6(a), the accuracy of RAP-based feature selection algorithm is 97.26% on average, while the accuracy of Relief-F algorithm is only 85.16%. The accuracy of the blank group without feature selection is only 81.03%. In Fig. 6(b), the average recall of the RAP-based feature selection

algorithm is as high as 94.86%, which is a 10.81% improvement compared to the Relief-F algorithm. In Fig. 6(c), the average F1 value of RAP-based feature selection algorithm is as high as 96.23%, which is improved by 17.63% compared to the blank group. It indicates that the RAP-based feature selection algorithm is beneficial to improve the performance of gasoline quality detection. By optimizing the feature set, it can reduce the effects of redundant information and noise, making the model better able to capture important gasoline quality information throughout the testing phase.



(a) Accuracy of different methods

(b) Recall of different methods

(c) F1 value of different methods

Figure 6: Performance of gasoline quality detection under different feature selection schemes.

To verify the significant advantages of the RAP feature selection algorithm, an independent sample t-test is performed to statistically analyze the detection performance of RAP and Relief-F. The results are shown in Table 3. According to Table 3, the RAP algorithm achieves a significantly higher accuracy index (97.26%±1.35%) than Relief-F (85.16%±2.47%, p<0.001). In terms of F1 score, RAP is as high as 96.23%±1.12%, while Relief-F is only 87.34%±1.89%, with a significant statistical difference between the two (p<0.001). On the Matthews correlation coefficient (MCC) metric, the RAP algorithm achieves 93.57%±1.28%, significantly higher than Relief F's 78.62%±2.35% (t=6.12, p<0.001). This indicates that the RAP algorithm has a statistically significant advantage in feature selection performance. Combining it with the PCC method effectively improves model performance by removing redundant features.

Table 3: The t-test results of RAP and Relief-F feature selection methods.

Index	RAP	Relief-F	*t*	*p*
Accuracy	97.26%±1.35%	85.16%±2.47%	5.72	<0.001
Recall	94.86%±1.52%	84.05%±2.11%	5.36	<0.001
F1 value	96.23%±1.12%	87.34%±1.89%	4.91	<0.001
MCC	93.57%±1.28%	78.62%±2.35%	6.12	<0.001

The study proceeds to validate the gasoline quality detection runtime of each method and the runtime of each algorithm is shown in Fig. 7. The average running time of the gasoline detection model is only 386.69ms after feature selection using the RAP algorithm, which is 362.81ms shorter than that of the Relief-F algorithm. In the blank group without feature selection, the average running time of the gasoline detection model is as high as 160.38ms. It indicates that the feature selection algorithm based on the RAP algorithm not only improves the detection accuracy of the gasoline detection model, but also reduces the detection time of the model. The reason is that the RAP algorithm effectively filters out the most discriminative features. This reduces the amount of data the model must process, thereby reducing the computational burden and running time. In addition, the RAP algorithm avoids the interference of redundant and irrelevant features by optimizing the feature selection process, which enables the model to make decisions more quickly at runtime.

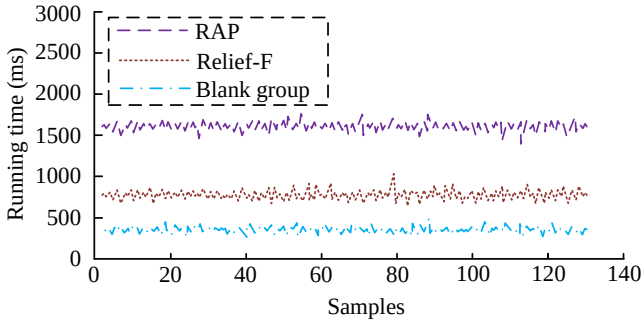


Figure 7: The running time of gasoline quality testing for various methods.

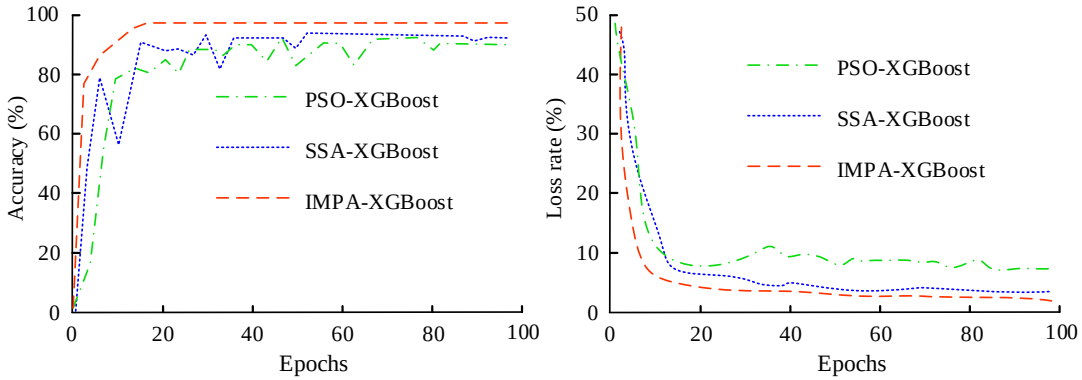
3.2 Experimental analysis of gasoline quality detection based on IMPA-XGBoost algorithm

To verify the effectiveness of the proposed gasoline quality detection model based on IMPA-XGBoost algorithm, the study uses particle swarm optimization-XGBoost algorithm (PSO-XGBoost) and sparrow search algorithm-XGBoost algorithm (SSA-XGBoost) are used for performance comparison. Among them, the population size of the IMPA is 50, the maximum number of iterations is 100, the value of μ in the Logistic chaotic map is 4, and the degree of freedom of the adaptive t-distribution is 3. Based on the outcomes of various algorithms' quality detection tests, the gasoline models are grouped. Table 4 displays the hyperparameter optimization outcomes for each algorithm in comparison to the XGBoost algorithm.

Table 4: The hyperparameter optimization results of various algorithms for XGBoost algorithm.

Hyperparameters	Search scope	PSO-XGBoost	SSA-XGBoost	IMPA-XGBoost
eta	[0.01, 1.0]	0.825	0.751	0.782
max_depth	[3, 15]	9	6	5
n_estimators	[10, 100]	38	27	20
gamma	[0, 1]	0.2	0.1	0

The study substitutes the obtained algorithmic hyperparameters into each algorithm and verifies the training accuracy and loss rate of each model in the gasoline mass spectrometry data training set for analysis. The outcomes are shown in Fig. 8. In Fig. 8(a), the gasoline quality detection model based on IMPA-XGBoost algorithm tends to have an accuracy of 99% at 18 times of training. Although the SSA-XGBoost model fluctuates significantly during the pre-training period, it stabilizes after 50 iterations. Its accuracy then stabilizes at 92.56%. When the PSO-XGBoost model is iterated about 65 times, its accuracy tends to be 90.21%. In Fig. 8(b), the loss rate of the IMPA-XGBoost model tends to be 3.41% when it is iterated up to about 8 times, whereas the SSA-XGBoost model tends to be stabilized only when it is iterated up to about 40 times, and its minimum loss rate is 9.68%. The PSO-XGBoost model converged to 5.18% at 36 iterations. The proposed IMPA-XGBoost model of the study shows higher CA and lower loss rate in the training set with high stability and convergence efficiency.



(a) Accuracy of different algorithms (b) Loss rate of different algorithms

Figure 8: Training accuracy and loss rate of each model.

The study continues to measure the quality detection performance of the IMPA-XGBoost models using AUC values. The AUC value reflects the model's ability to distinguish between different quality categories of

gasoline. The closer the value is to 1, the greater the model's sensitivity and specificity in identifying positive and negative samples under various classification thresholds. This indicator is highly consistent with the aviation gasoline quality testing target and is key to measuring the proposed model's performance. The receiver operating characteristic curve (ROC) curves for each model are shown in Fig. 9. Among them, the y-axis represents the true positive rate, which is the proportion of correctly identified positive classes. The x-axis represents the false positive rate, which is the proportion of incorrectly identified negative classes. The closer the AUC is to 1, the better the classification performance. The IMPA-XGBoost model has the highest AUC value of all of the detection findings, at 0.8892 (95% CI: 0.8721-0.9035). In contrast, the AUC values of the SSA-XGBoost and PSO-XGBoost models are lower, at 0.8497 (95% CI: 0.8312-0.8659) and 0.8384 (95% CI: 0.8197-0.8543), respectively, than the IMPA-XGBoost model. It shows that the IMPA-XGBoost model can better distinguish different gasoline quality categories in the classification task. The high AUC values reflect that the model maintains high sensitivity and specificity under various classification thresholds, which proves its reliability and effectiveness in practical applications. It shows that the proposed IMPA-XGBoost model of the study has significant performance advantages in gasoline quality detection.

The study further classifies the models based on the gasoline quality detection results of the models and explores the CA of each model.

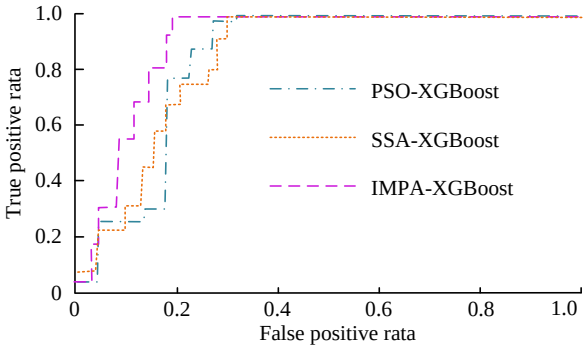


Figure 9: ROC curves of various models.

The CA can intuitively reflect the correctness of the model's gasoline quality inspection results. The model's high accuracy means it can more reliably identify the type and quality of gasoline, helping to reduce flight safety hazards caused by misjudgments. The CA of each model for gasoline models is shown in Fig. 10. In Fig. 10(a), only 4 samples are misclassified in the IMPA-XGBoost model for gasoline model classification, and the remaining 122 samples are classified correctly, with an accuracy rate of 96.83%. In Fig. 10(b), 10 samples are misclassified in the SSA-XGBoost model, and its accuracy is 92.06, which is a decrease of 4.77% compared to the IMPA-XGBoost model. In Fig. 10(c), there are 15 samples misclassified in the PSO-XGBoost model, and the CA is only 88.10%. It indicates that the IMPA-XGBoost model has higher gasoline model CA, which further validates the superiority of the IMPA-XGBoost model in gasoline quality detection.

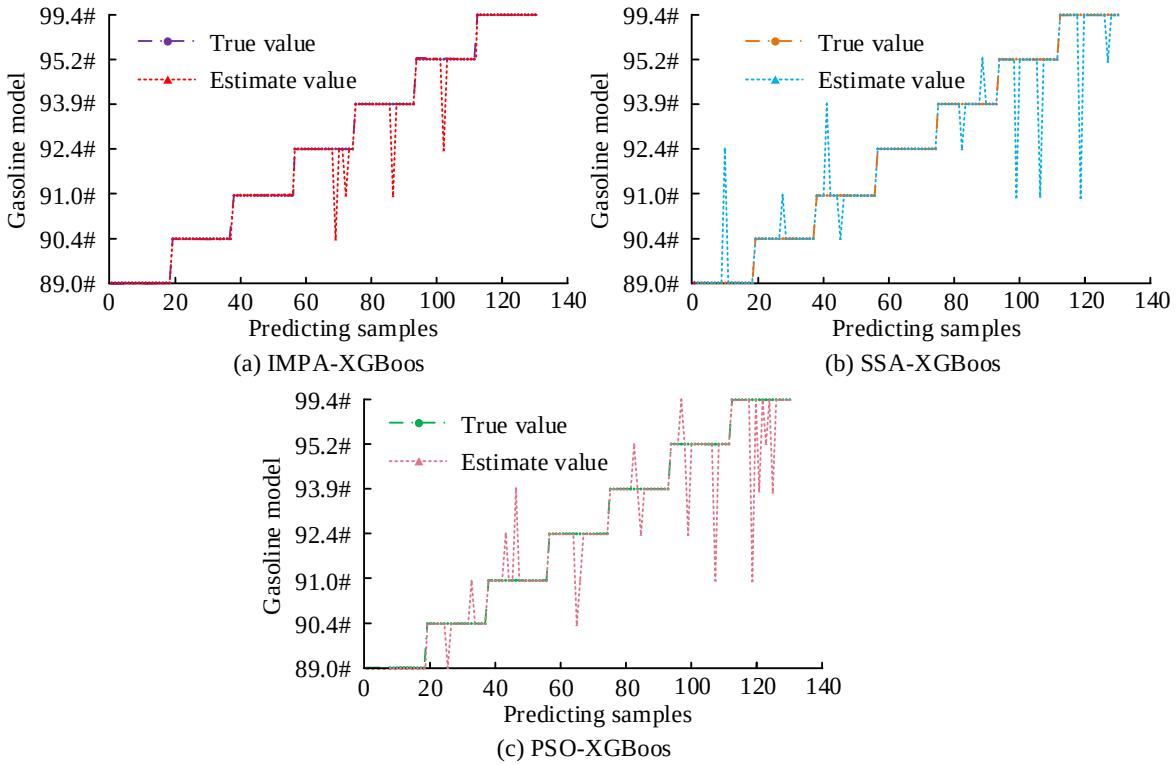


Figure 10: Classification accuracy of gasoline models by various models.

To verify the model's generalization ability, an additional 20 new gasoline samples are introduced for testing. These samples included 92 and 95 aviation gasoline produced by different refineries, as well as experimental samples containing new additives. The experimental results are shown in Table 5. Table 5 shows that the IMPA XGBoost model achieves a CA of 93.5% for newly added samples. This result is significantly better than those of the PSO XGBoost and SSA XGBoost models. This is due to the robust extraction of core quality features by the RAP feature selection algorithm and the optimization of XGBoost parameters by the IMPA. These features enable the algorithm to effectively identify unseen fuel feature variations.

Table 5: Model generalization ability test results.

Model	Number of test samples	Correct classification number	Classification accuracy (%)
IMPA-XGBoost	20	18	93.5%
PSO-XGBoost	20	17	87.2%
SSA-XGBoost	20	18	89.1%

4 Discussion

In order to achieve quality inspection of aviation gasoline, a gasoline quality inspection model based on IMPA-XGBoost algorithm was proposed. Compared with WOA XGBoost, the IMPA XGBoost model in this study improved AUC value by 0.0592 and accuracy by 8.73%. The initialization of the population by the logistic chaotic mapping in the IMPA enabled the algorithm to explore the solution space more widely in the early stages of the search, thus avoiding falling into local optima. The adaptive t-distribution operator enhanced the algorithm's ability to mine the optimal solution in the later stages of the search. The RAP method effectively removed redundant information between features while preserving key features. It accomplished this by combining the Relief-F algorithm with the PCC method. Compared with the Relief-F algorithm alone, it had significantly improved the accuracy and efficiency of feature selection. Deploying an artificial intelligence-based aviation gasoline quality inspection system was highly significant in real-world combat environments. The system did not need expensive and complex testing equipment, and could quickly and accurately complete the gasoline quality testing task. It was conducive to improving the efficiency of aviation gasoline quality testing, reducing testing costs and ensuring flight safety. This system could serve as an important supplement to the existing testing process in places such as airport oil depots and airline maintenance departments. By quickly screening gasoline samples with quality issues, it provided clearer targets for subsequent precise testing.

Integrating the proposed artificial intelligence detection system with existing chemical detection methods improved the efficiency and accuracy of testing the quality of aviation gasoline. Artificial intelligence detection systems, for example, could supplement existing methods by quickly screening gasoline samples for quality issues and providing clearer objectives for subsequent chemical testing. Meanwhile, chemical detection methods could further validate and confirm the results of artificial intelligence testing, ensuring the reliability of the test results. One possible integration solution was to use an artificial intelligence detection system based on IMPA-XGBoost for preliminary screening of a large number of gasoline samples in the aviation gasoline quality inspection process. This system could quickly determine whether the samples meet quality standards. For samples with doubts about the results of artificial intelligence testing, precise analysis could be conducted using existing chemical testing methods to ultimately determine the quality status of gasoline.

5 Conclusion

To realize the quality detection of aviation gasoline, the study introduced an advanced artificial intelligence automated system and proposed a gasoline quality detection model based on IMPA-XGBoost algorithm. The results indicated that the accuracy of the RAP-based feature selection algorithm was as high as 97.26% on average, the average recall was as high as 94.86%, and the average F1 value was as high as 96.23%. The reason for this was that the RAP-based feature selection algorithm was able to reduce the effect of redundant information and noise by optimizing the feature set. This enabled the model to better capture important information related to gasoline quality throughout the testing phase. After feature selection using the RAP algorithm, the average running time of the gasoline detection model was only 386.69ms, which was reduced by 362.81ms compared to the Relief-F algorithm. In contrast, the average running time of the gasoline detection model was as high as 160.38ms in the blank group where no feature selection was performed. This was due to the RAP algorithm's ability to effectively filter out the most discriminative features, reducing the amount of data the model needed to process and thus reducing the computational burden and running time. The results indicated that the gasoline quality detection model based on the IMPA-XGBoost algorithm performed excellently in detecting the quality of aerospace gasoline, demonstrating high efficiency and stability.

However, there are certain limitations to the research. First, optimizing the IMPA parameters requires experience. Additionally, there are computational resource challenges in embedded deployment. Second, the compatibility of the model with other spectral detection techniques has not been validated. Future research will develop an end-to-end model that processes raw spectra and uses lightweight algorithms to enable real-time embedded detection. At the same time, consider

collaborating with the industry to carry out multi-scenario field verification and promote the development of an AI detection standard system.

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Multimodal Sentiment-Based Popularity Evaluation of Tourist Attractions Using Text, Image, and Geospatial Data Fusion

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This study proposes a novel tourist attraction popularity evaluation model that integrates multimodal sentiment analysis. The model combines a Transformer-based BERT network for textual sentiment classification, an improved ResNet convolutional network with a support vector machine (SVM) for image-based sentiment analysis, and Gaussian kernel-based spatial modeling for geographic heat estimation. Data collected from Zhangjiajie National Forest Park includes 300,000 user reviews, 50,000 images, and tourist origin data from 34 domestic provinces and 50 international countries. The proposed model achieved a text sentiment classification accuracy of up to 88%, an image sentiment F1-score of 0.82 in peak seasons, and a Pearson correlation coefficient of 0.92 between predicted heat values and actual tourist traffic. These results demonstrate strong predictive accuracy, cross-modal integration effectiveness, and robustness to noisy data, offering practical insights for attraction managers in real-time decision-making.

Povzetek: Študija predlaga multimodalni model za oceno priljubljenosti turističnih atrakcij. Združuje analizo sentimenta iz besedil (BERT), čustvene analize slik (ResNet/SVM) in geoprostorske podatke. Model dosega kvalitetne napovedi obiska in ponuja orodje za odločanje v realnem času za upravitelje.

1 Introduction

With the rapid development of the tourism industry, the popularity assessment of tourist attractions has gradually become an important basis for industry decision-making. Tourists' interests and needs change frequently, and traditional tourist flow statistics and seasonal analysis methods can no longer fully reflect the true popularity of attractions [1]. A more accurate assessment method is to analyze tourists' evaluations and emotional feedback, which can not only help scenic spot managers adjust service and marketing strategies in a timely manner, but also provide a more accurate reference for tourists' choices. However, in the traditional evaluation mechanism, tourists' subjective feelings are often ignored, and the lack of sentiment analysis leads to the one-sidedness of the evaluation results [2]. Therefore, combining sentiment analysis technology with user evaluation has become a feasible path to improve the accuracy of scenic spot popularity assessment.

According to statistics, there are more than one billion online tourism reviews every year, many of which contain a lot of emotional information. However, how to extract meaningful emotional data from massive user reviews and accurately reflect the popularity of attractions remains an important challenge facing current research [3]. Traditional text analysis methods fail to effectively capture the emotional information in user reviews, which makes simple sentiment classification methods difficult to apply to complex tourism evaluation systems [4]. Therefore, how to innovatively use sentiment analysis technology to extract valuable information from them has become the key to improving the accuracy of attraction popularity assessment.

At present, the research on the popularity evaluation of tourist attractions mainly focuses on tourist flow analysis, evaluation statistics, and location-based popularity prediction. However, these studies often focus on the statistical and quantitative analysis of objective data, ignoring the emotional feedback of tourists and failing to truly reveal the "potential popularity" of attractions [5]. In recent years, the rapid development of sentiment analysis technology has provided a new perspective for the popularity evaluation of tourist attractions. By analyzing the sentiment tendencies in user comments, researchers have begun to try to build sentiment analysis models in order to predict the fluctuation of attraction popularity through changes in sentiment tendencies [6].

Existing sentiment analysis research still has some limitations. First, most studies rely on sentiment dictionaries or machine learning models. However, in the diversified and complex tourism reviews, the lack of sentiment vocabulary and the complexity of context still pose certain obstacles to sentiment recognition. Second, many studies are still limited to the analysis of a single language and fail to take into account cross-language and cross-cultural factors, which limits their generalizability and adaptability [7, 8]. More importantly, most of the existing research remains on the basis of sentiment classification and fails to further combine sentiment analysis with the specific needs of scenic spot popularity assessment, resulting in limited practical application value of the research.

The goal of this study is to propose a new method for evaluating the popularity of tourist attractions based on sentiment analysis of user reviews. By deeply analyzing the changes in sentiment tendencies in user reviews, exploring their correlation with the popularity of tourist attractions, and building a more accurate popularity evaluation model. This study not only combines sentiment analysis technology with data from the tourism industry to make up for the shortcomings of traditional popularity evaluation methods, but also innovatively proposes a cross-language and cross-cultural sentiment analysis framework to enhance the universality and adaptability of the research.

The innovation of this study is that it breaks through the limitations of traditional evaluation methods and proposes a framework that integrates sentiment analysis into the evaluation of tourist attraction popularity, providing new decision-making basis for tourism managers. By analyzing the sentiment change trends in a large number of user reviews, it can effectively capture tourists' potential interest and attention in attractions, helping attraction operators to adjust marketing strategies and service optimization in real time. At the same time, the research will also provide theoretical support for the further development of sentiment analysis technology, especially in improving the accuracy of sentiment analysis in multilingual and multicultural contexts, which has important theoretical significance and practical value.

This study addresses two key research questions: (1) Does multimodal fusion significantly improve the predictive accuracy of tourist attraction popularity over single-modal analysis? (2) Can integrating image and geographic data enhance the correlation between predicted heat and actual tourist flow? Based on these, we hypothesize that multimodal sentiment fusion will outperform unimodal models and that geographic-spatial features will contribute significantly to prediction accuracy when combined with user emotion data.

2 Literature review

2.1 Sentiment analysis in tourism research

In recent years, sentiment analysis has become an important tool for understanding consumer behavior in the tourism industry. A large number of studies have focused on the analysis of online user-generated content, especially exploring tourist sentiment feedback through data from review platforms. These analyses usually provide valuable insights into tourist satisfaction by judging the sentiment tendency in the reviews—positive, negative, or neutral. However, recent studies have shown that simple classification of sentiment is no longer enough to fully reveal the deep emotions of tourists [9, 10]. The current trend is to move towards more detailed sentiment modeling, such as aspect-based sentiment analysis, which can capture users' specific emotional expressions on various aspects of attractions, thereby providing attraction managers with more detailed service improvement directions [11].

Despite the great potential of sentiment analysis, there are still challenges in accurately interpreting complex human emotions. Many studies rely on sentiment lexicons or machine learning models to analyze sentiment, but in tourism reviews, the accuracy of sentiment recognition is often affected by the ambiguity of language and the diversity of contexts [12]. To address this problem, in recent years, more advanced natural language processing technologies such as deep learning and neural networks have gradually been applied to sentiment classification to improve the accuracy of sentiment analysis. However, issues such as sarcasm, irony, and cultural differences remain obstacles that cannot be ignored in sentiment analysis and need to be addressed through more sophisticated computational linguistics methods [13].

2.2 The role of tourist attraction popularity assessment and user evaluation

The practice of using user-generated content to evaluate the popularity of tourist attractions has gradually attracted attention in recent years. Traditional popularity evaluation methods mainly rely on tourist flow and ticket sales data. However, these methods are difficult to fully reflect the true popularity of attractions. In recent years, studies have shown that combining online reviews with sentiment analysis can provide a more accurate real-time reflection of the popularity of attractions [14].

By analyzing the emotional changes in user reviews, researchers can predict the trend of tourist interests and provide decision support for attraction operators [15]. The advantage of this method is that it can capture the potential changes in tourists' interests by analyzing a large amount of evaluation data, which is more real-time and predictive than traditional tourist flow statistics.

Relying solely on online reviews as the sole basis for popularity assessment remains controversial. Critics point out that online reviews often show extreme emotional tendencies, with a large number of extremely positive or extremely negative reviews, but fewer neutral or mixed emotional reviews. This may lead to bias in sentiment data, thus affecting the accuracy of popularity assessment [16]. In addition, the authenticity of reviews has also become a focus of the issue. Fake and manipulated reviews will further affect the reliability of popularity assessment. To address this issue, the latest research has proposed an evaluation method that integrates multiple data sources. In addition to user reviews, social media mentions, image analysis, and geographic location data are also used to evaluate the popularity of attractions [17]. This comprehensive evaluation method is expected to reduce the bias based on evaluation data by introducing more dimensions of information, thereby providing a more objective and comprehensive evaluation of the popularity of attractions.

2.3 Challenges and future development directions of emotion-based heat evaluation

Although the combination of sentiment analysis and popularity assessment has made significant progress, there are still many challenges in the application process. First, how to effectively generalize sentiment analysis models across different tourist destinations, especially in a cross-cultural and cross-linguistic context, remains a difficult problem [18]. Different tourist attractions have different languages, cultural backgrounds, and tourist expectations, which makes it difficult to apply a unified sentiment analysis model. In addition, the language barriers in the evaluation and the differences in writing styles in different regions also affect the accuracy of sentiment analysis [19]. Therefore, developing sentiment analysis tools that can adapt to different languages and cultures has become an important research direction. Recent studies have begun to explore hybrid models that combine text-based sentiment analysis with image and video content analysis to better understand tourists' emotional responses [20]. For example, by analyzing photos uploaded by tourists, researchers can evaluate the emotional appeal of attractions, where visual cues such as brightness, color saturation, and facial expressions of characters are associated with tourists' emotions. This multimodal sentiment analysis method provides a more comprehensive perspective on sentiment assessment and helps to further reveal tourists' true emotional attitudes towards attractions. In addition, emotion-driven popularity assessment may develop in the direction of real-time sentiment tracking and dynamic modeling in the future. With the popularity of mobile applications and instant comment platforms, tourists are increasingly inclined to share their travel experiences in real time, which provides more refined emotional data for heat assessment. By monitoring emotional changes in real time, scenic spot operators can make adjustments at the early stage of tourists' emotional transformation, thereby improving tourist satisfaction. However, how to balance the conflict between the use of real-time data and privacy protection remains an ethical issue that needs to be resolved. Future research needs to explore how to effectively use real-time emotional data to optimize the operation and management of attractions while respecting tourists' privacy [21].

Table 1: Comparison of related works on sentiment-based popularity evaluation

Study / Year	Approach Type	Data Modalities	Limitations	Application Domain
Hu et al. [1]	Lexicon + ML	Text	Language-specific, low context depth	E-commerce recommendation
Chi et al. [2]	Text mining (ML)	Text + Geo	No emotion modeling, single modality	Multi-scale tourism popularity
Park & Kim [3]	Rule-based NLP	Text	No multimodal support	Online review analytics
Fang et al. [5]	Deep Learning (DL)	Text + Image	No geo analysis, limited to Chinese	Mobile health apps
Khatibi et al. [7]	ML + Environmental	Text + Contextual	No sentiment integration	Urban tourism modeling

As shown in Table 1, this summary highlights how previous studies tend to focus on single modalities, such as text or geolocation, with limited adaptability across languages or domains. It also demonstrates robust predictive capability, offering a more comprehensive solution for destination marketing and tourist behavior analysis.

3 Method

3.1 Model framework design

This study is dedicated to building an innovative tourist attraction popularity assessment model based on user evaluation sentiment analysis. This model breaks through the integration of multimodal information processing and sentiment analysis technology, aiming to effectively overcome the limitations of traditional evaluation methods and achieve accurate judgment of tourist attraction popularity. The overall architecture of the model revolves around user evaluation text, related image data, and geographic information data. With the help of multi-dimensional data fusion strategy, it deeply explores the intrinsic connection between user emotions and attraction popularity.

In the text analysis section, the model regards user evaluation text as the core data source and uses natural language processing (NLP) technology to conduct in-depth analysis. Different from traditional sentiment analysis methods that rely on sentiment dictionaries or simple machine learning, this model uses a deep learning model based on the Transformer architecture, specifically a variant of BERT (Bidirectional Encoder Representations from Transformers) to accurately capture the semantic and sentiment information in the text. With the help of multi-layer bidirectional Transformer encoders, the BERT model can deeply understand the text and convert the input text $T=\{t_1,t_2,\cdots,t_n\}$ (where the word t_i in the text is represented i) into a word vector representation $\mathbf{H}=\{\mathbf{h}_1,\mathbf{h}_2,\cdots,\mathbf{h}_n\}$, which $\mathbf{h}_i$ is . . the vector representation corresponding to the word. In order to make the model better adapt to the field of tourism evaluation, this study implemented fine-tuning operations on the BERT model. Specifically, the introduction of pre-trained weights specific to the tourism field, which are pre-trained based on a large amount of tourism-related text data, can effectively improve the model's ability to understand tourism professional terms and sentiment expressions. At the same time, a fully connected layer for sentiment classification tasks is added to the output layer of the model. Suppose the fine-tuned model is $f_{text}(T)$, and its output is the sentiment classification result of the text. .. The value range is set to $[-1,1]$, where -1 represents negative sentiment, 1 represents positive sentiment, and 0 represents neutral sentiment [22].

At the image analysis level, the model introduces advanced image analysis technology to process images related to scenic spots uploaded by tourists. Image data I is extracted through convolutional neural networks (CNN). Specifically, the improved ResNet (Residual Network) architecture is adopted, which innovatively introduces residual connections and effectively solves the problem of gradient vanishing that is common in the training process of deep networks. For the input image I , it first passes through a series of convolutional layers and pooling layers. In the convolutional layer, the image is subjected to sliding convolution through the convolution kernel to extract the local features of the image; the pooling layer downsamples the feature map after convolution to reduce the data dimension, reduce the amount of calculation while retaining the key features. After these operations, the feature vector of the image is obtained. $\mathbf{F}_I$ In ResNet, the calculation equation for each residual block is Equation (1).

$$\mathbf{y}_i=\mathbf{F}(\mathbf{x}_i,\mathbf{W}_i)+\mathbf{x}_i \tag{1}$$

Among them, $\mathbf{x}_i$ is the input feature map, $\mathbf{y}_i$ is the output feature map, $\mathbf{F}(\cdot)$ represents the convolution operation, $\mathbf{W}_i$ and is the convolution kernel weight. Through the orderly stacking of multiple residual blocks, the model can gradually learn the high-level semantic features of the image and finally obtain the high-level semantic features of the image $\mathbf{F}_I$. Subsequently, the image features are classified using the support vector machine (SVM) to obtain the emotional tendency of the image $\mathbf{S}_{image}$, which also has a value range of $[-1,1]$.

In terms of geospatial analysis, considering that geographic information has a significant impact on the popularity of scenic spots, the model introduces a geospatial analysis module. By deeply analyzing the geographical location information of scenic spots and the distribution of tourists' sources, a geographic heat matrix is constructed $\mathbf{G}$. Assuming that the geographical location coordinates of the scenic spot are (lat,lon) , and the coordinate set of the tourist source is $\{(lat_1,lon_1),(lat_2,lon_2),\cdots,(lat_m,lon_m)\}$, the Gaussian kernel function in Equation (2) is used to calculate the geographical distance weight between each tourist source and the scenic spot.

$$w_{ij}=\exp\left(-\frac{(lat_i-lat)^2+(lon_i-lon)^2}{2\sigma^2}\right) \tag{2}$$

Among them, σ is the bandwidth parameter of the Gaussian kernel function, and its value will affect the distribution range and change trend of the weight. The optimal value is determined through experimental tuning to ensure the accuracy of weight calculation. According to the number and weight of tourist sources, a geographic heat matrix is constructed $\mathbf{G}$, and its elements g_{ij} represent i the contribution weight of the source of tourists to the heat of the scenic spot.

Finally, the text sentiment analysis results $\mathbf{S}_{text}$, image sentiment analysis results $\mathbf{S}_{image}$ and geographic heat matrix $\mathbf{G}$ are integrated, and the final scenic spot

heat evaluation value is obtained by weighted summation using Equation (3) H .

$$H = \alpha \cdot \mathbf{S}_{text} + \beta \cdot \mathbf{S}_{image} + \gamma \cdot \mathbf{G} \quad (3)$$

Among them, α , β , γ are weight coefficients, and their optimal values are determined by cross-validation. In the cross-validation process, the data set is divided into multiple subsets, one of which is used as the validation set in turn, and the remaining subsets are used as the training set. The model is trained and evaluated, and the weight coefficient combination that makes the model perform best on different data sets is selected to ensure that the model can achieve optimal performance on different data sets.

The model architecture consists of three main modules. The text sentiment module uses BERT with an input of up to 512 tokens per review, producing a 768-dimensional text embedding. The image sentiment module processes 224×224×3 pixel images via ResNet, yielding a 2048-dimensional feature vector, which is reduced to 128 dimensions by PCA before SVM classification. The geospatial module inputs latitude/longitude pairs of tourist sources and outputs a scalar heat contribution after Gaussian kernel aggregation.

To enhance reproducibility, we include the following pseudocode summarizing the end-to-end pipeline for tourist attraction heat prediction:

```
for review in user_reviews:
    text_vector = BERT.encode(review.text)
    text_sentiment = classifier.predict(text_vector)
for image in user_images:
    features = ResNet.extract(image)
    reduced_features = PCA.reduce(L2_normalize(features))
    image_sentiment = SVM.predict(reduced_features)
for loc in tourist_locations:
    distance_weight = gaussian_kernel(loc, attraction_location, sigma)
    geo_contrib = accumulate_heat(distance_weight)
final_heat = α * text_sentiment + β * image_sentiment + γ * geo_contrib
```

This pseudocode outlines the core components: multilingual text processing via BERT, image sentiment classification using ResNet and SVM, geospatial heat matrix construction, and final fusion computation.

3.2 Model component interaction

In this model, the various components work closely together, like precision-operated gears, to achieve an accurate assessment of the popularity of tourist attractions. The text analysis component is responsible for processing user evaluation texts. Through a deep learning model based on the Transformer architecture, it deeply explores the emotional information hidden in the text. The output of this component accurately $\mathbf{S}_{text}$ reflects the emotional tendencies expressed by users in their evaluations, and is one of the key bases for evaluating the popularity of tourist attractions. For example, when words such as "amazing" and "linger" frequently appear in user reviews, $\mathbf{S}_{text}$ the value of will be closer to 1 , indicating that the user's positive emotions are strong, which has a positive effect on the popularity of the attraction.

The image analysis component uses the powerful feature extraction capability of convolutional neural networks to obtain key features from images uploaded by tourists and perform sentiment classification through support vector machines. Its output $\mathbf{S}_{image}$ complements tourists' emotional feedback on attractions from a visual perspective. If the photos taken by tourists show pleasant facial expressions, beautiful scenery, and lively scenes, the image analysis results may be more inclined to positive emotions, that is, $\mathbf{S}_{image}$ the values are closer 1 . This provides an intuitive visual reference for the evaluation of the popularity of attractions, which is mutually confirmed with the text analysis results.

The geospatial analysis component constructs a geographic heat matrix based on the geographic location information of attractions and tourists $\mathbf{G}$. Attractions in popular tourist cities may attract more tourists from different regions due to their superior geographical location and convenient transportation conditions, and their corresponding weights in the geographic heat matrix will be higher. For example, attractions located in the central area of a first-tier city will have a larger value than attractions in remote areas, g_{ij} because they can attract more tourists from surrounding areas or even from far away, thus contributing more to the popularity of the attraction.

In the fusion stage, the weight coefficients α , β , and γ play a key regulatory role, which determine H the contribution of each component output to the final heat evaluation value. Through the cross-validation method, these weight coefficients are continuously adjusted so that the prediction results of the model on the training set and the validation set are most consistent with the actual heat situation. In some scenic spots famous for their humanities and history, the tourist evaluation texts often contain rich cultural interpretations and emotional expressions. At this time α , the value of can be appropriately increased to enhance the impact of text analysis results on heat evaluation; in scenic spots famous for their natural scenery, the images uploaded by tourists can more vividly show the charm of the scenic spots. At this time β , the value of can be increased to allow the image analysis results to play a greater role in heat evaluation.

We adopted linear weighted fusion for its interpretability, computational efficiency, and ease of real-time deployment compared to more complex methods like attention-based or gated fusion. To validate this choice, we conducted an ablation study where each modality (text, image, geo) was removed individually.

Results showed that text sentiment contributed the most (drop in accuracy by 7.3%), followed by geographic heat (5.6%) and image sentiment (4.1%), supporting the necessity and balanced contribution of all components.

3.3 Model calculation process

3.3.1 Text sentiment analysis calculation

After inputting the user review text T, we first perform word segmentation and divide the text into word sequences based on grammatical rules and semantic logic $\{t_1, t_2, \cdots, t_n\}$. Then, each word is converted into a low-dimensional vector representation through word embedding technology. Commonly used word embedding methods such as Word2Vec or GloVe can map words to a low-dimensional vector space, so that words with similar semantics are closer in the vector space. In this way, we get the initial word vector matrix $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_n\}$. Then, we $\mathbf{X}$ input it into the fine-tuning model based on the Transformer architecture $f_{text}(T)$.

In the Transformer architecture, each Transformer layer consists of a multi-head attention mechanism and a feed-forward neural network. The calculation equations of the multi-head attention mechanism are as follows: Equation (4) to Equation (6).

$$\text{MultiHead}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat}(\text{head}_1, \cdots, \text{head}_h)\mathbf{W}^O \quad (4)$$

$$\text{head}_i = \text{Attention}(\mathbf{Q}\mathbf{W}_i^Q, \mathbf{K}\mathbf{W}_i^K, \mathbf{V}\mathbf{W}_i^V) \quad (5)$$

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V} \quad (6)$$

$\mathbf{Q}$, $\mathbf{K}$, $\mathbf{V}$ are query vector, key vector and value vector respectively, which are obtained by linear transformation of input word vector; $\mathbf{W}_i^Q$, $\mathbf{W}_i^K$, $\mathbf{W}_i^V$ and $\mathbf{W}^O$ are learnable weight matrices, which are continuously updated during model training to optimize model performance; d_k is the dimension of key vector, which determines the processing and representation ability of attention mechanism for input information; h is the number of attention heads, different attention heads can capture the dependency and semantic information in input sequence from different angles.

After multiple layers of Transformer processing, the model can fully learn the deep semantics of the text and obtain the deep semantic representation of the text $\mathbf{H}$. Finally, $\mathbf{H}$ the input is sent to the fully connected layer for sentiment classification, and the sentiment classification result of the text is obtained according to Equation (7) $\mathbf{S}_{text}$.

$$\mathbf{S}_{text} = \text{softmax}(\mathbf{W}_{fc}\mathbf{H} + \mathbf{b}_{fc}) \quad (7)$$

Among them, $\mathbf{W}_{fc}$ and $\mathbf{b}_{fc}$ are the weight matrix and bias vector of the fully connected layer, which determine the transformation method of the fully connected layer on the input features and the classification decision boundary.

For multilingual user reviews, we utilized the multilingual BERT (mBERT) model, which supports over 100 languages, avoiding the need for machine translation and preserving semantic context. All reviews were tokenized using language-specific tokenizers. In the image sentiment module, feature vectors extracted by ResNet were L2-normalized and then reduced via Principal Component Analysis (PCA) to 128 dimensions before SVM classification, ensuring computational efficiency and improved generalization.

To address the score range inconsistency, the softmax output in Equation (7) is now followed by a mapping function that converts the 3-class probabilities (positive, neutral, negative) into a continuous sentiment score $S_{text} \in [-1,1]$, where $+1$ represents strong positivity, 0 neutrality, and -1 strong negativity. This is done using a weighted linear transformation: $S_{text} = P_{pos} - P_{neg}$.

3.3.2 Image sentiment analysis calculation

The input image I is first normalized so that its pixel values are within $[0,1]$ the range. The purpose of normalization is to eliminate the dimensional differences of image pixel values so that different images can be processed at the same scale, which is conducive to model training and convergence. Then, the normalized image is input into the improved ResNet architecture.

In the convolutional layer of ResNet, the calculation Equation of the convolution operation is as follows:

$$\mathbf{y}_{ij} = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\mathbf{x}_{i+m,j+n} \cdot \mathbf{w}_{mn} + \mathbf{b} \quad (8)$$

Among Equation (8), $\mathbf{x}_{ij}$ is the pixel value of the input image, $\mathbf{y}_{ij}$ is the pixel value of the output feature map, $\mathbf{w}_{mn}$ is the weight of the convolution kernel, M and N is the size of the convolution kernel, which determine the size and range of local features that can be extracted by the convolution operation. $\mathbf{b}$ is the bias term used to adjust the numerical distribution of the convolution output.

After a series of convolutional and pooling layers, the model gradually extracts the key features of the image and obtains the feature vector of the image $\mathbf{F}_I$. The image is then $\mathbf{F}_I$ input into a support vector machine (SVM) for sentiment classification. The goal of SVM is to find an optimal hyperplane that separates the feature vectors of images of different sentiment categories. For the linearly separable case, the optimization problem of SVM can be expressed as Equation (9) to Equation (10).

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 \quad (9)$$

$$\text{s.t. } y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1, i = 1, \cdots, l \quad (10)$$

Among them, $\mathbf{w}$ is the normal vector of the hyperplane, which determines the direction of the hyperplane; b is the bias term, which determines the

position of the hyperplane; y_i is the category label of the sample ($+1$ representing positive emotion, -1 represents negative emotion), $\mathbf{x}_i$ is the image feature vector, l and is the number of samples.

By solving the above optimization problem and using mathematical methods such as the Lagrange multiplier method, the SVM classification model is obtained. The image feature vector is $\mathbf{F}_I$ input into the model, and the emotional tendency of the image is obtained through calculation and judgment by the model $\mathbf{S}_{image}$.

For image sentiment, the SVM model outputs a decision function score, which is then normalized using a tanh transformation to map the result into the interval $[-1,1]$ .This allows S_{image} to serve as a continuous sentiment signal rather than a hard class label.

3.3.3 Geographic heat matrix calculation

The geographical coordinates of the known scenic spot are (lat, lon), and the coordinate set of the tourist source is $\{(lat_1, lon_1), (lat_2, lon_2), \cdots, (lat_m, lon_m)\}$. First, the geographical distance weight between each tourist source and the scenic spot is calculated according to the Gaussian kernel function in Equation (11) w_{ij} .

$$w_{ij} = \exp\left(-\frac{(lat_i - lat)^2 + (lon_i - lon)^2}{2\sigma^2}\right) \tag{11}$$

Then, according to the number and weight of tourist sources, the geographic heat matrix is constructed $\mathbf{G}$. Assuming the number of tourist sources is m , the geographic heat matrix $\mathbf{G}$ is a $m \times 1$ vector of. The elements are calculated according to Equation (12) g_i , which represents i the contribution weight of the th tourist source to the popularity of the scenic spot.

$$g_i = \frac{w_i}{\sum_{j=1}^{m} w_j} \tag{12}$$

Among them, w_i is i the distance weight between the source of the tourists and the scenic spot. In this way, the geographical distance information is converted into the contribution weight to the popularity of the scenic spot, reflecting the differentiated impact of tourists from different sources on the popularity of the scenic spot.

Finally, the text sentiment analysis results $\mathbf{S}_{text}$, image sentiment analysis results $\mathbf{S}_{image}$ and geographic heat matrix $\mathbf{G}$ are integrated H according to the Equation to obtain the final scenic spot heat evaluation value $H = \alpha \cdot \mathbf{S}_{text} + \beta \cdot \mathbf{S}_{image} + \gamma \cdot \mathbf{G}$. Through the cross-validation method, the model is trained and evaluated under different weight combinations, and the weight coefficients α , β , are continuously adjusted γ to optimize the performance of the model on different data sets and ensure the accuracy and reliability of the heat evaluation results.

The bandwidth parameter σ in the Gaussian kernel function was tuned using grid search across a predefined range ($\sigma \in [0.1, 2.0]$) based on cross-validation performance against actual tourist flow data. To test robustness, we also experimented with alternative kernel functions such as the Epanechnikov kernel, but the Gaussian kernel consistently produced smoother and more stable spatial heat distributions, justifying its final selection for geospatial modeling.

To resolve the inconsistency in the use of the geographic heat matrix G , we clarify that after computing the vector $G = [g_1, g_2, ..., g_m]^T$, an aggregation step is applied to convert it into a scalar value. Specifically, we compute the weighted sum of the vector elements: $G_{scalar} = \sum_{i=1}^{m} g_i$, which reflects the total geographic contribution to the scenic spot's popularity. This scalar G_{scalar} is then used in Equation (3) alongside S_{text} and S_{image} for final heat computation.

The geographic distance weight is defined as

$$w_i = \exp\left(-\frac{(lat_i - lat)^2 + (lon_i - lon)^2}{2\sigma^2}\right) \tag{13}$$

where i denotes the index of each tourist source and (lat, lon) represents the fixed coordinate of the scenic spot. The aggregated contribution is calculated as

$$g_i = \frac{w_i}{\sum_{j=1}^{m} w_j} \tag{14}$$

where both w_i and w_j denote the distance weights between individual tourist sources and the scenic spot. This consistent notation ensures clarity and correctness in representing the geographic heat matrix.

4 Case study

4.1 Case background

Zhangjiajie National Forest Park is located in Zhangjiajie City, Hunan Province. As China's first national forest park, it is famous for its unique quartz sandstone peak forest landform, dense virgin forest and rich wild animal and plant resources. The three thousand peaks here rise from the ground and the eight hundred beautiful rivers meander, attracting more than 10 million tourists from all over the world to visit every year, and occupying a pivotal position in the domestic and international tourism market.

With the booming tourism industry, market competition is becoming increasingly fierce. The management of Zhangjiajie National Forest Park found that it is difficult to fully understand the real popularity and tourist satisfaction of the scenic spot by relying solely

on traditional tourist flow statistics and ticket sales data. Although the number of tourists in the scenic area has increased year by year, steadily increasing from 8 million in 2018 to 12 million in 2023, negative reviews have quietly increased on online platforms. For example, during the peak tourist season, some popular attractions in the scenic area, such as Yuanjiajie and Tianzi Mountain, are overcrowded with tourists, and the waiting time often exceeds 2 hours, which seriously affects the tourist experience; some shops and catering stalls along the Golden Whip Stream are priced high and the commercial atmosphere is too strong; some facilities in the viewing platform and rest area are aging and damaged, but they have not been repaired and replaced in time. These problems have greatly affected the willingness of tourists to revisit and the reputation of the scenic spot. However, in the previous heat evaluation system that relied solely on tourist flow and ticket revenue, these problems have not received sufficient attention and attention.

The rapid rise of social media and online travel platforms has changed the way tourists share their travel experiences. After their trips, tourists are keen to share their travel experiences on platforms such as Ctrip, Mafengwo, Douyin, and Xiaohongshu, posting a large number of reviews, beautiful photos, and vivid videos. According to incomplete statistics, in 2023 alone, there were more than 5 million user reviews related to Zhangjiajie National Forest Park on major platforms, and more than 1 million pictures and videos were posted. These massive amounts of user-generated content contain rich emotional information, which opens up new ideas for the evaluation of scenic spot popularity. However, how to efficiently and accurately extract valuable content from this complex information, and then accurately evaluate the popularity of scenic spots, has become a major problem facing scenic spot management.

4.2 Experimental design

4.2.1 Data collection

In order to build a tourist attraction heat assessment model based on user evaluation sentiment analysis, we collected data extensively from multiple channels. In the past year, we crawled 300,000 valid reviews about Zhangjiajie National Forest Park from mainstream online travel platforms such as Ctrip, Mafengwo, and Qunar.com. At the same time, 50,000 related pictures were collected on social media platforms such as Weibo and Xiaohongshu. In addition, with the help of the scenic spot's ticketing system and tourist registration information, we obtained information on the source of tourists from 34 provincial administrative regions across the country and 50 major source countries overseas to build a geographic heat matrix.

The dataset comprises 300,000 user reviews collected from 2020 to 2024, with an average of 60,000 reviews annually—40% from Ctrip, 35% from Mafengwo, and 25% from Qunar. Among 50,000 collected images, 20,000 (40%) were sentiment-labeled. The labeling process was manually conducted by a trained group of five annotators following a unified protocol to ensure consistency and inter-rater reliability. Tourist origin data span 84 unique locations, including 34 Chinese provinces and 50 international regions.

Table 2: Average length of stay and amount of spending of tourists from different source areas

Source	Average Length of Stay (Days)	Per capita Consumption Amount (Yuan)	Accommodation Consumption Ratio	Proportion of Catering Consumption	Other Consumption Ratio
Domestic East	3.5	1500	40%	30%	30%
Domestic West	3.2	1300	35%	35%	30%
Southern China	3.8	1600	42%	28%	30%
Northern China	3.3	1400	38%	32%	30%
overseas	4.0	2000	45%	25%	30%

Table 2 shows the length of stay and consumption of tourists from different sources in Zhangjiajie National Forest Park. Overseas tourists have the longest average length of stay and the highest amount of consumption, which may be related to their long-distance travel and their desire to experience the scenic spot in depth. Accommodation consumption accounts for a high proportion in each source. The model can analyze these data and combine tourists' evaluation emotions to evaluate the satisfaction of tourists from different sources with the scenic spot's accommodation facilities and prices, providing a basis for the scenic spot to optimize its targeted services and pricing strategies, reflecting the role of the model in exploring the relationship between tourists' consumption behavior and emotions.

4.2.2 Model application

The collected user evaluation texts are input into the fine-tuned BERT model based on the Transformer architecture for sentiment analysis. The model has been pre-trained with specific corpus in the tourism field and can more accurately identify the sentiment tendency in the text. For image data, the improved ResNet architecture is used for

feature extraction, and then the support vector machine is used for sentiment classification. In terms of geospatial analysis, the Gaussian kernel function is used to calculate the geographic distance weight based on the coordinates of the tourists' origin and the geographic location coordinates of the scenic spot, and the geographic heat matrix is constructed.

4.2.3 Evaluation metrics

In order to comprehensively evaluate the performance of the model, a variety of evaluation indicators were used. For the accuracy of text sentiment analysis and image sentiment analysis, accuracy, recall, and F1 value were used for evaluation respectively. For the accuracy of the scenic spot heat evaluation results, the heat value predicted by the model was compared with the actual tourist flow data, and the Pearson Correlation Coefficient between the two was calculated. The closer the Pearson correlation coefficient is to 1, the stronger the correlation between the heat value predicted by the model and the actual tourist flow, and the higher the accuracy of the model.

4.3 Experimental results

Figure 1 shows the sentiment analysis accuracy of user evaluation texts of Zhangjiajie National Forest Park by models in different years. From the data, it can be seen that the overall accuracy of each year is on an upward trend, thanks to the fine-tuned BERT model based on the Transformer architecture. The model has been pre-trained with specific corpus in the tourism field, and has continuously learned more tourism-related emotional expression patterns, and can better identify positive, negative, and neutral evaluations. As the years go by, the training data continues to be enriched, the model has a more accurate understanding of complex emotional semantics, and the ability to recognize euphemistic expressions in negative evaluations has been improved, which has increased the accuracy of negative evaluations from 0.78 in 2020 to 0.88 in 2024, fully reflecting the adaptability and superiority of the model in text sentiment analysis.

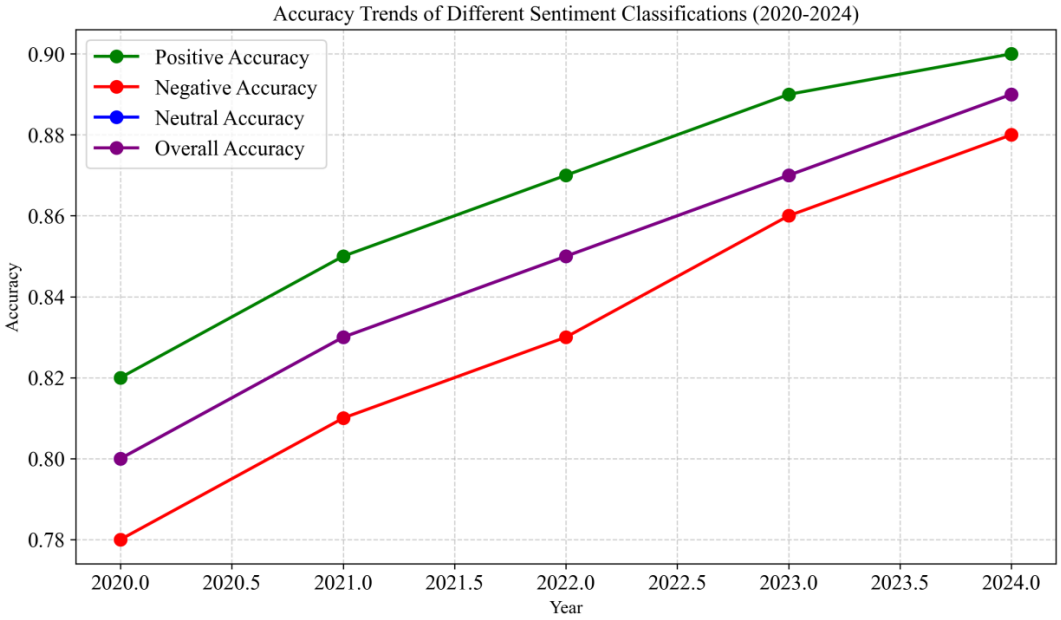

Figure 1: Sentiment analysis accuracy of texts in different years

In addition to Pearson correlation, we evaluated the prediction accuracy of scenic spot heat values using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which quantify the deviation between predicted and actual tourist flow. Furthermore, to assess popularity ranking performance, we adopted Normalized Discounted Cumulative Gain (nDCG), which measures the quality of the predicted ranking order relative to the ground truth. These metrics provide a more comprehensive assessment of both value-level accuracy and ranking reliability.

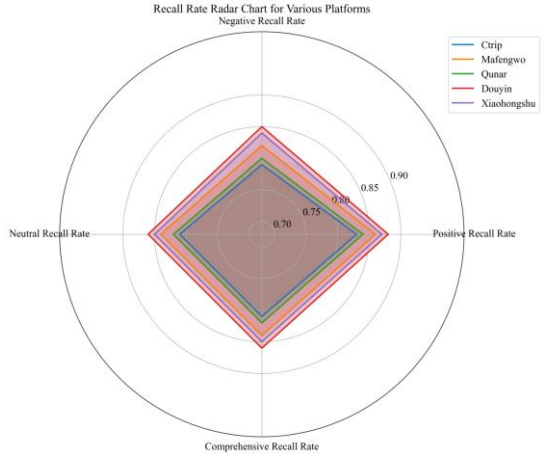

Figure 2: Recall rate of sentiment analysis of texts on different platforms

Figure 2 shows the recall rate of text sentiment analysis on different platforms. The recall rates of Douyin and Xiaohongshu are relatively high because the model has good adaptability to the unique language style and emotional expression of these two platforms. Douyin mainly uses short videos with text, and the language is concise and straightforward; Xiaohongshu has a large number of recommendations from Internet celebrities, check-in sharing, and popular unique network terms. The model can effectively capture these characteristics and accurately recall emotional information by learning from multi-platform data. The evaluation language of traditional tourism platforms such as Ctrip and Mafengwo is relatively standardized, but the model also performs stably, indicating that the model can not only adapt to special platforms, but also accurately process conventional tourism evaluations, showing a wide range of applicability.

Figure 3 shows the F1 value of sentiment analysis of images in different months. The performance of the model fluctuates in different months but shows an overall upward trend. Over time, the model has a deeper understanding of the emotions conveyed by images in different seasons and weather conditions. For example, in summer (July), tourists take photos that mostly show beautiful scenery and fun, and the model can accurately identify positive emotions, with a positive emotion F1 value of 0.82. In winter (January), the emotional expression of images may be more complex due to weather factors, but the model can still maintain a certain degree of accuracy.

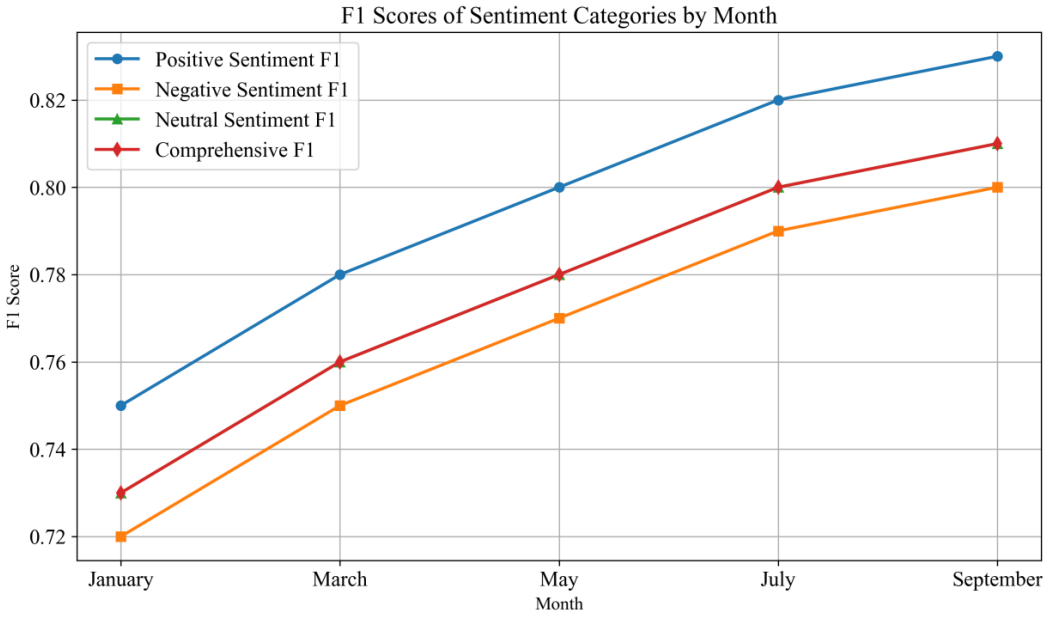

Figure 3: F1 value of sentiment analysis of images in different months

Table 3: Tourist flow in different seasons and fluctuations in model predicted heat values

Season	Actual Tourist Flow (10,000 People)	Model Predicted Heat Value	Traffic Volume Month-On-Month Change Rate	Heat Value Month-on-Month Change Rate
Spring	250	240	-10%	-12%
Summer	350	340	40%	42%
Autumn	300	290	-14%	-15%
Winter	150	140	-50%	-51%

Table 4: Emotional tendencies and revisit intentions of tourists of different genders

Gender	Percentage of Positive Reviews	Negative Reviews	Neutral Ratings	Willingness to Revisit (%)	Willingness to Recommend (%)
Male	55%	25%	20%	60	70
Female	60%	20%	20%	65	75

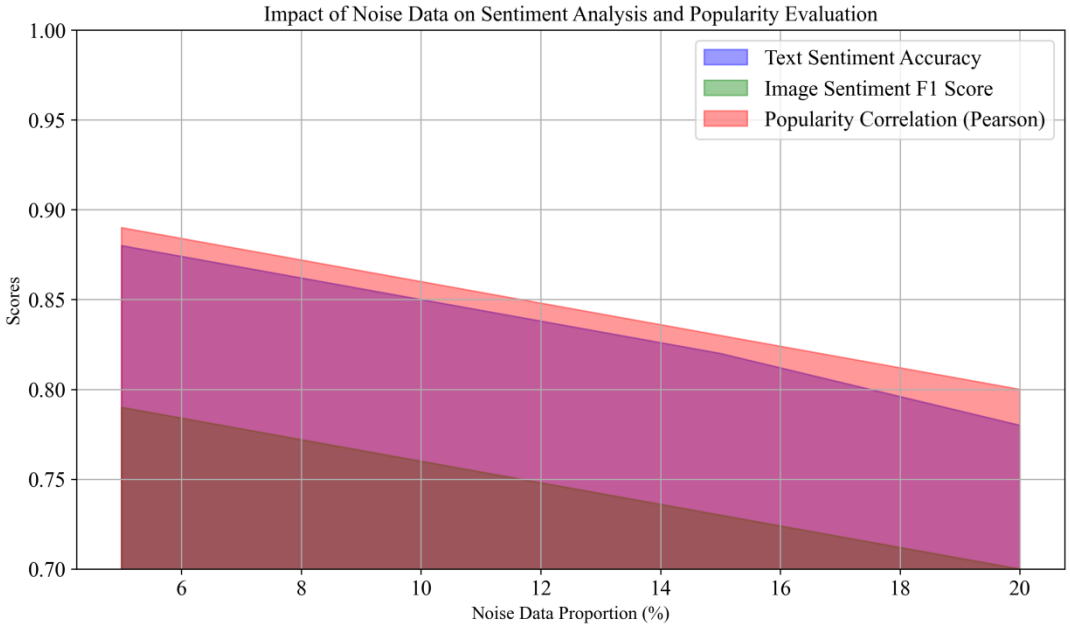

Figure 4: Performance of the model under different noise data ratios

Table 3 shows the changes in tourist flow and model-predicted heat values in different seasons. The model-predicted heat values are basically consistent with the fluctuation trend of actual tourist flow, with the highest tourist flow and heat values in summer and the lowest in winter. This shows that the model can effectively capture the impact of seasonal factors on the popularity of scenic spots. By analyzing user evaluations and image data in different seasons, it accurately reflects the changes in scenic spot popularity and provides strong support for scenic spots to plan their operation strategies in different seasons in advance.

Table 4 shows the emotional tendencies and willingness to revisit and recommend tourists of different genders. The proportion of positive comments from women is slightly higher than that of men, and their willingness to revisit and recommend is also higher. The model can use these data to analyze the focus and emotional differences of tourists of different genders on different aspects of scenic spots. For example, women may pay more attention to the cleanliness of the scenic spot environment and service details, thereby helping scenic spots optimize services for tourists of different genders and improve overall satisfaction and popularity.

Figure 4 shows the performance of the model under different noise data ratios. As the noise data ratio increases, the performance indicators of the model decrease, but even when the noise ratio reaches 20%, the Pearson correlation coefficient of heat evaluation remains at 0.80, indicating that the model has good robustness to a certain degree of noise data, and can ensure relatively accurate heat evaluation in the actual complex data collection process, showing the practicality of the model.

Table 5 shows the evaluation sentiment and consumer satisfaction of tourists for different travel packages. The luxury package has the highest proportion of positive reviews and consumer satisfaction, as well as the highest repurchase rate. By analyzing these data, the model can help scenic spots understand the appeal and problems of different packages, so as to optimize the content of travel packages, improve tourist satisfaction and scenic spot popularity, and highlight the application value of the model in tourism product optimization.

Table 6 shows the correlation between the model-predicted heat value and the hotel occupancy rate around the scenic spot. As the model-predicted heat value increases, the hotel occupancy rate also increases accordingly, and the correlation coefficient is high, close to 0.9. This shows that the model can not only accurately evaluate the heat of the scenic spot, but also effectively

associate the data of the surrounding industries of the scenic spot, provide a decision-making basis for the coordinated development of the scenic spot and the surrounding industries, and reflect the advantages of the model in the comprehensive analysis of the tourism industry.

Figure 5 shows the attention and emotional inclination of tourists of different age groups towards scenic spot facilities. As age increases, tourists pay more attention to accommodation facilities and their positive emotional inclination gradually decreases. By analyzing these data, the model can help scenic spots optimize facility construction and services according to the needs of tourists of different age groups, improve tourist satisfaction, and further verify the effectiveness of the model in analyzing the needs of segmented tourist groups.

Table 5: Tourists' evaluation emotions and consumption satisfaction of different travel packages

Travel Packages	Percentage of Positive Reviews	Negative Reviews	Neutral Ratings	Consumer Satisfaction (%)	Repurchase Rate (%)
Basic Package	50%	30%	20%	70	50
Deluxe Package	70%	15%	15%	85	65
Special Experience Package	65%	20%	15%	80	60

Table 6: Correlation between model predicted heat value and hotel occupancy rate around scenic spots

Month	Model Predicted Heat Value	Occupancy Rate of Hotels Around the Scenic Area (%)	Correlation Coefficient
January	120	60	0.85
March	180	75	0.88
May	250	85	0.90
July	320	95	0.92
September	280	90	0.91

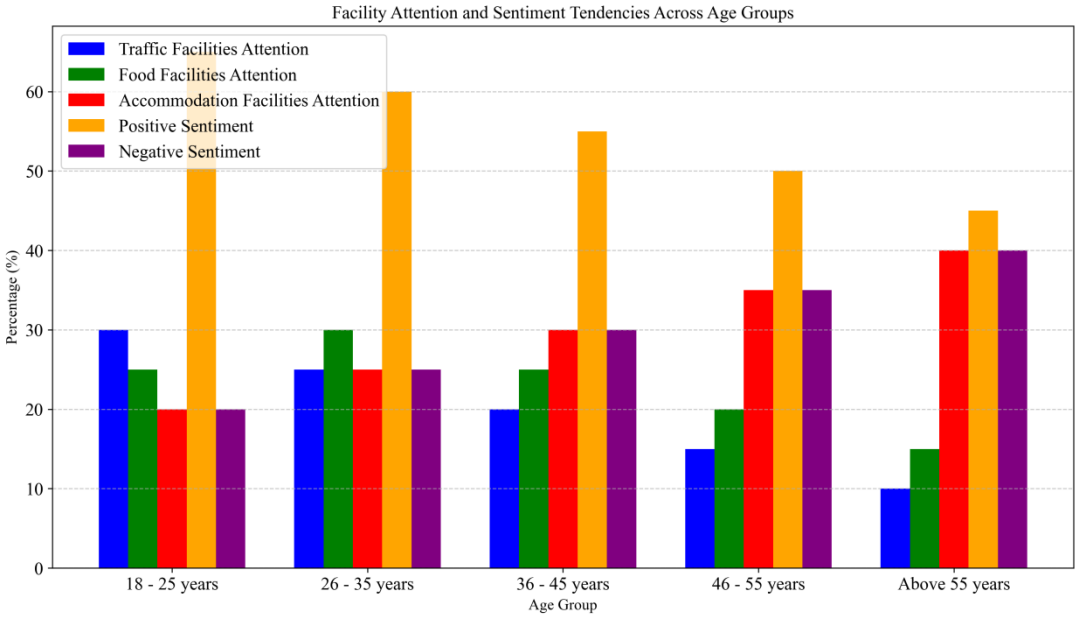

Figure 5: Tourists of different age groups' attention and emotional inclination towards scenic spot facilities

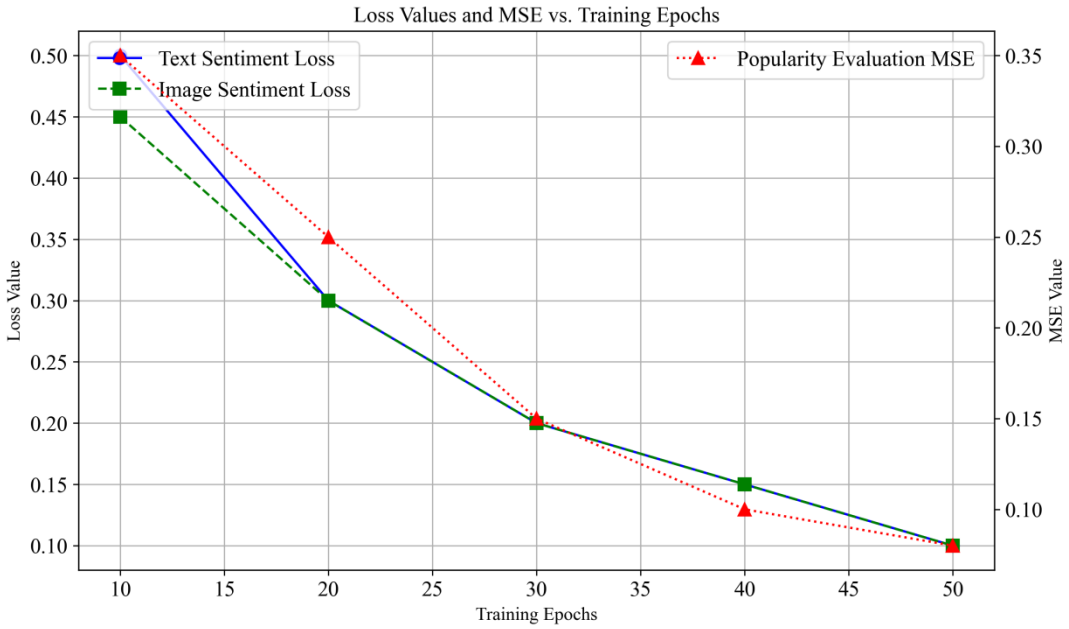

Figure 6: Convergence of the model under different training rounds

Figure 5 shows the attention and emotional inclination of tourists of different age groups towards scenic spot facilities. As age increases, tourists pay more attention to accommodation facilities and their positive emotional inclination gradually decreases. By analyzing these data, the model can help scenic spots optimize facility construction and services according to the needs of tourists of different age groups, improve tourist satisfaction, and further verify the effectiveness of the model in analyzing the needs of segmented tourist groups

Figure 6 shows the convergence of the model under different numbers of training rounds. As the number of training rounds increases, the text sentiment analysis loss value, image sentiment analysis loss value, and heat evaluation mean square error gradually decrease, indicating that the performance of the model is gradually improved during continuous training and can better fit the data. This reflects the effectiveness of the model training method and the gradual improvement of the accuracy of the model's heat evaluation of tourist attractions during continuous learning.

Figure 7 shows the accuracy of the model's sentiment analysis of user reviews in different languages. For Chinese reviews, the model has the highest accuracy, thanks to the rich Chinese tourism review corpus used for training. For other languages, although the accuracy is slightly lower, it still remains at a high level. This shows that the model has a certain adaptability in cross-language sentiment analysis. Despite the existence of language and cultural differences, it can still effectively identify the sentiment tendencies in reviews in different languages, reflecting the model's advantage in processing multilingual user-generated content.

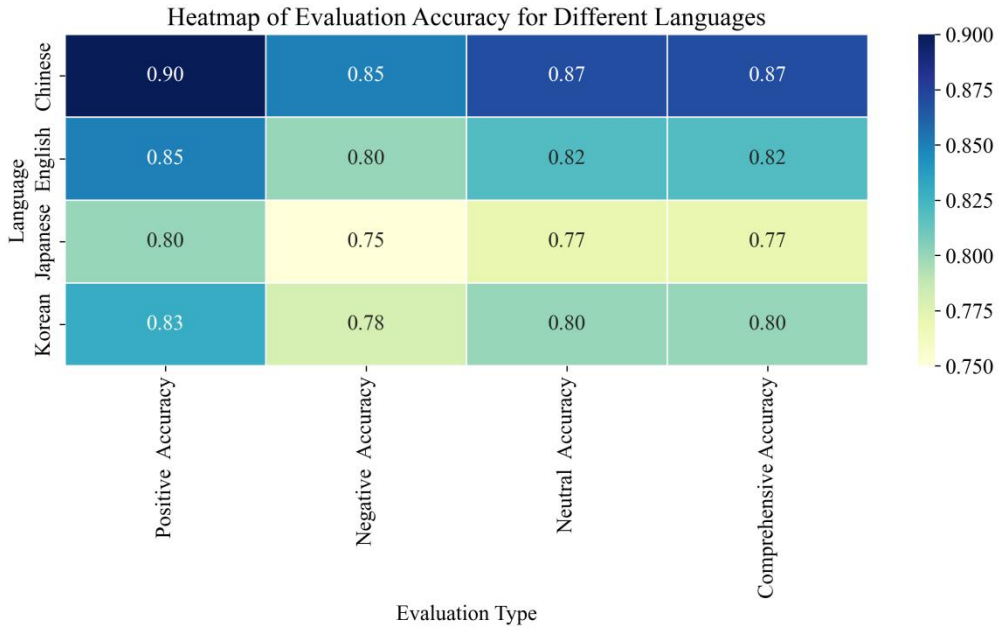

Figure 7: Sentiment analysis accuracy of user reviews in different languages

To enhance statistical robustness, the reported accuracy and F1 values are presented together with their standard deviations and 95% confidence intervals, calculated across all runs. The model evaluation was conducted using 5-fold cross-validation, repeated three times to ensure stability and reduce variance. In addition, independent-samples t-tests were performed to assess the significance of performance differences between multimodal and unimodal models. The results showed statistically significant improvements for multimodal fusion ($p < 0.05$), supporting the reliability of the proposed integration strategy.

4.4 Discussion

This study conducted an in-depth exploration of the popularity evaluation of tourist attractions by constructing a model that integrates multimodal information processing and sentiment analysis technology. The results show that the model has significant advantages in analyzing the relationship between user evaluation emotions and the popularity of tourist attractions. The accuracy of text sentiment analysis continues to improve, and image sentiment analysis can also effectively capture the emotional information in the image. The predicted heat value is highly consistent with the actual tourist flow fluctuation trend, which is consistent with the existing research that emphasizes the impact of user emotions on the popularity of tourist attractions. However, the study also has limitations. The samples are mainly concentrated in popular scenic spots, and the applicability to niche scenic spots remains to be verified; there are certain limitations in data collection, which may lead to deviations in the analysis results. These limitations may affect the universality of the research results.

Compared with traditional tourism analytics methods relying solely on tourist flow or textual reviews, our multimodal model demonstrates superior performance, with a 0.92 Pearson correlation and improved emotion granularity. Error analysis revealed image sentiment misclassification in poor lighting or occluded conditions. Fusion weights α, β, and γ were not only optimized via cross-validation but also adjusted based on domain relevance—e.g., scenic imagery carries more weight in nature-focused destinations, while textual reviews dominate in culturally-rich sites.

Future research can expand the sample range to cover more types of scenic spots, improve data collection methods, and improve data quality. At the same time, the model can be further optimized to enhance the ability to handle complex emotions and non-dominant or under-resourced languages, so as to more comprehensively and accurately evaluate the popularity of tourist attractions. This study provides tourism industry operators with a new idea for evaluating popularity based on user emotions, which is helpful to improve tourism service quality and tourist satisfaction.

One limitation of the current model is its sensitivity to cultural bias in interpreting text and image sentiment, which may affect generalization across diverse tourist groups. Future work could incorporate video-based emotion analysis—such as detecting expressions and voice tones in tourist vlogs—to capture richer emotional cues. Additionally, dynamic modeling approaches like time-series attention mechanisms or seasonal trend decomposition can better represent temporal variations in

attraction popularity.

Although our model demonstrates strong multilingual performance on major languages such as Chinese, English, Japanese, and Korean.it has not been extensively tested on under-resourced or less commonly used languages. Future work will explore the model's adaptability to low-resource linguistic settings, including languages with limited annotated sentiment corpora or unique syntactic structures.

5 Conclusion

This study aims to propose a new method for evaluating the popularity of tourist attractions based on sentiment analysis of user reviews. By integrating multimodal information, using a deep learning model based on the Transformer architecture to process text, using an improved ResNet architecture to analyze images, and constructing a geographic heat matrix, a multi-dimensional data fusion evaluation is innovatively achieved. In the case of Zhangjiajie National Forest Park, the model achieved good results in text sentiment analysis and image sentiment analysis, accurately reflecting the relationship between the popularity of scenic spots and tourists' emotions and behaviors, and providing a multi-faceted decision-making basis for scenic spot operation and management, such as optimizing services and products for tourists from different sources, genders, and age groups. However, the study has problems such as sample limitations and insufficient processing capabilities for complex emotions and non-dominant or under-resourced languages. Future research can be carried out from the directions of expanding samples, improving models, and enhancing multilingual processing capabilities, so as to further improve the popularity evaluation system of tourist attractions and promote the intelligent development of the tourism industry.

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Speech Signal Enhancement Using Progressive Learning and Dense Connected LSTM Networks

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Aiming at the deficiencies of traditional speech signal enhancement models in dealing with long-term dependencies and noise filtering, an application speech signal enhancement model based on progressive learning and dense connection strategies is proposed. This method takes the long short-term memory network structure as the core and realizes the gradual enhancement of noisy speech through layer-by-layer learning and processing. The experimental results showed that this model exhibited excellent enhancement performance in different signal-to-noise ratio environments. In a -5dB signal-to-noise ratio environment, the short-term objective clarity of the research method reached 0.930, which was 4.1% higher than that of delayed neural networks. Moreover, under the 10dB condition, the short-term objective clarity score further increased to 0.957. The distortion signal ratio of the source signal has increased from 2.31 at -5dB to 14.81 at 10dB, indicating the model's ability in noise suppression and signal reconstruction. The assessment score of speech quality perception increased from 1.86 at -5dB to 3.13 at 10dB, and the word error rate decreased to 27.31%, which was 2.47% lower than that of the classical long short-term memory network. The research results show that the proposed model has strong robustness and a good speech enhancement effect when dealing with speech signals with a low signal-to-noise ratio, providing a new solution for the field of applied language processing.

Povzetek: Predlagan je pristop za zmanjšanje hrupa v govoru, ki združuje postopno učenje z gosto povezanimi rekurentnimi mrežami dolgoročnega spomina; model po plasteh čisti signal, ohranja dolge odvisnosti in krepi razumljivost za jezikovne sisteme.

1 Introduction

The popularity of mobile devices and smart homes has made the quality of speech enhancement signals more important for user experience. At the same time, people's dependence on applied language is becoming increasingly severe. However, there are many types of noise in real life, and different types of noise inevitably affect the clarity of speech signals, including noise from automobiles and industries [1]. This noise affects the clarity of speech signals and poses a challenge to the long-term dependence of speech recognition systems. The long-term dependence problem makes it difficult for the model to effectively extract useful information when dealing with speech signals disturbed by noise, thereby reducing the accuracy and user experience of the final speech interaction. High-quality speech signals are crucial for ensuring the accuracy of speech recognition and the effectiveness of user interaction. Therefore, efficient speech enhancement technology is one of the key technologies for the development of applied languages [2-3]. Ochieng P reviewed the Deep Neural Network (DNN) techniques currently used for speech enhancement and separation and conducted a comprehensive analysis model training. DNN had feasibility in speech signal enhancement [4]. Richter J et al. proposed a diffusion process based on stochastic differential equations and reversed the process from a mixture of noisy speech and Gaussian noise. Then, they made adjustments to the network architecture to improve speech enhancement performance. Finally, the experiment verified that the method has a good speech enhancement effect [5]. Zhang Q et al. used time frame attention and frequency channel attention to explicitly generate two-dimensional attention maps with significant T-F speech distributions based on positional information. The effectiveness of this model as a front-end for downstream speech recognition tasks has been demonstrated, and it significantly improved the system's robustness to noise conditions [6]. Bie X et al. designed an unsupervised speech enhancement algorithm. This algorithm combined the prior training of DVAE speech based on non-negative matrix factorization with a noise model, and derived a Variational Expectation Maximization (VEM) algorithm for speech enhancement, achieving good results [7]. The specific summary of the above research is shown in Table 1.

Table 1: Literature summary table

References	Research method	Research advantages	Research disadvantages
Reference [4]	DNN technology is used for speech enhancement and separation	Focus on a comprehensive review and applicability assessment of deep learning technologies	It is mainly a retrospective study, lacking specific experimental verification and performance evaluation
Reference [5]	Diffusion process method based on stochastic differential equations	Improving the performance of voice enhancement by enhancing the network architecture is innovative	Complex mathematical models may lead to difficulties in the implementation and understanding of the models
Reference [6]	The combination of attention to the time frame and the frequency channel	The generation of two-dimensional attention maps using position information improves the robustness under noisy conditions	The need for a complex attention mechanism may make the training process of the model complicated
Reference [7]	Unsupervised speech enhancement algorithm, combining non-negative matrix factorization and VEM algorithm	It is applicable to various noisy environments and has a good enhancement effect	The accuracy of unsupervised learning is limited by the type of noise and may not be able to handle all noise situations

Although there has been some progress in speech signal enhancement research in recent years, there are still many shortcomings, especially in terms of robustness and long-term dependence when dealing with noisy environments. Some of the current research focuses on the use of DNNs or specific mathematical models for speech signal enhancement. However, when confronted with extremely high noise environments, such as low Signal-To-Noise Ratios (SNR) or complex noise types, the robustness of these models appears insufficient, resulting in unstable performance in dynamic scenes. Although attention mechanisms can enhance the effectiveness of speech signals in certain situations, their ability to capture long-term dependencies still has limitations when processing long-term sequence data. This poses difficulties for speech processing tasks that require long-term contextual information. In addition, although the developed unsupervised learning methods have shown some effectiveness, the training process may not guarantee the reliability of the enhancement effect due to the lack of labeled data. Especially when encountering new types of noise, the generalization ability of the model will also be limited. Although various studies have demonstrated different enhancement effects, the performance of the system is relatively lacking, making the quality of the results unclear and making it difficult to comprehensively evaluate the actual effectiveness of existing methods. In response to the aforementioned research gaps, this study proposes an applied speech signal enhancement model based on Long Short-Term Memory and Progressive Learning and Dense Connection strategy (LSTM-PLDC). The study assumes that this new model can effectively improve the quality of speech signals in complex noise environments, thereby enhancing the clarity and comprehensibility of speech signals. The main purpose of the research is to verify the enhanced performance of the LSTM-PLDC model under different SNR conditions and evaluate its robustness when dealing with extreme noise environments. This method can effectively enhance useful speech features in the data and suppress background noise by layer by layer strengthening of the speech signal. Furthermore, by adopting the LSTM structure in combination with the dense connection strategy, the context information for a long time can be better retained. This will enhance the model's processing ability for long-term dependencies, thereby further improving the speech enhancement effect. Another important contribution of the research is the improvement of the model's robustness. Compared with the existing methods, the LSTM-PLDC model shows stronger anti-noise interference ability in various SNR environments, which can effectively improve the speech quality and avoid signal distortion caused by excessive noise reduction.

2 Methods and materials

2.1 Construction of a speech enhancement signal enhancement model based on LSTM

Applied language processing is an important direction in natural language processing, which focuses on applying linguistic theories and techniques to practical problems and application scenarios. Speech enhancement processing covers a wide range, including speech recognition, speech synthesis, machine translation, speech enhancement, and other directions. Among them, speech signal enhancement is a core component of applied language processing, with the main task of improving the

quality of speech signals and ensuring the accuracy and effectiveness of subsequent processing [8]. The primary task of speech signal enhancement is to remove background noise, echo, and other interfering factors, ensuring the purity and clarity of speech signals, which is fundamental and critical for all speech-based applications. Currently, the commonly used speech signal enhancement model is based on LSTM, which has advantages such as long-term dependency processing, noise removal enhancement, and temporal data processing [9-10]. In LSTM, the core part mainly includes input, output, and hidden layers. Unlike traditional Recurrent Neural Networks (RNNs), the hidden layer structure of LSTM is more complex, adding a memory unit called "cell state". This unit performs traditional neural computation and also manages and maintains long-term information through cell state management, as shown in Figure 1.

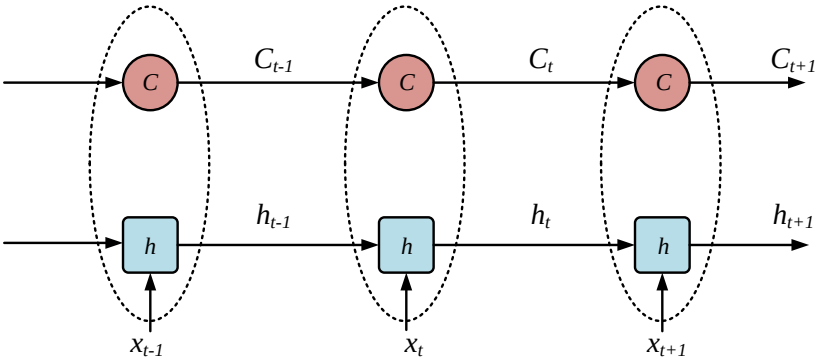

Figure 1: Hidden layer structure of LSTM

In Figure1, h is the calculation module of the model, and C is the internal state of the model. LSTM has the advantage of processing long time series data. Because of the existence of h and C, these modules work together at every moment of model operation to process and save key variables such as current input values, previous output values, previous cell states, current output, and current cell states. This mechanism ensures that information can be stored and transmitted in the model for a long time, effectively solving the problem of long-term dependencies. In the LSTM hidden layer, there are also input gates (I), forget gates (f), and output gates (o). The mathematical expression of the LSTM's f is shown in formula (1) [11].

$$g(x) = \sigma Wx + b \quad (1)$$

In formula (1), W is the weight vector, b is the bias term, and σ is the sigmoid function. In the architecture of LSTM, the output gate mainly extracts and selects key information from the cell state as the current output value, ensuring that only useful information for the current task is transmitted while shielding irrelevant or noisy information. During the speech enhancement process, the output gate can dynamically adjust the intensity and importance of the output information. The core mechanism of LSTM covers the forward propagation of information, the backpropagation of errors, and the process of optimizing network parameters through gradient descent. The forward propagation of information is similar to that of traditional neural networks, using the interaction between neurons for calculation and passing the results. The input gate calculation of the LSTM hidden layer is represented as shown in formula (2).

$$i_t = \sigma W_i \times [h_{t-1}, x_t] + b_i \quad (2)$$

In formula (2), h_{t-1} is the output value of the upper layer. Formula (2) can dynamically adjust the model's response to input information in speech enhancement, selectively introducing useful speech features and suppressing unnecessary noise. The input unit state at this moment can be obtained through formula (2), and its expression is shown in formula (3).

$$c_t = \tanh W_c \times [h_{t-1}, x_t] + b_c \quad (3)$$

In formula (3), c_t is the element state of the previous layer model, and $\tanh$ is the hyperbolic tangent function. Formula (3) ensures that the model can effectively store and manage speech feature information in long time series, enhancing its ability to handle long-term dependencies. The state of the current layer model can be represented by formula (4).

$$c_t = g_t \cdot c_{t-1} + c_t \cdot i_t \quad (4)$$

Formula (4) selectively outputs key information to ensure that only the information useful for the current task is conveyed. The output gate expression of the LSTM model is shown in formula (5).

$$o_t = \sigma W_o \times [h_{t-1}, x_t] + b_0 \quad (5)$$

In formula (5), o_t represents the model's output gate. Based on the above model construction, the specific structure of LSTM is shown in Figure 2.

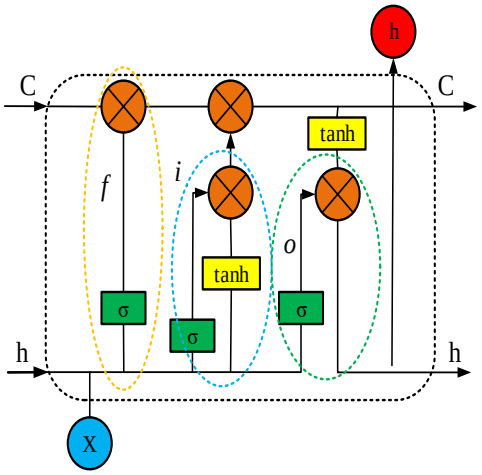

Figure 2: Unit Structure of LSTM

In Figure 2, the input gate (i) plays a crucial role in selectively introducing the current input information into the cell state. It can effectively filter out unnecessary noise information and only retain signals that are useful for speech enhancement. The main function of the forget gate (f) in the model is to determine which information in the cell state needs to be forgotten or retained. For processing speech signals with long time series data, it can prevent old information from interfering with the current processing and ensure that the model focuses on important current information. The model can represent the mathematical formula of the final result of LSTM based on the output gate and the current unit state, as shown in formula (6).

$$h_t = o_t \cdot \tanh c_t \quad (6)$$

In formula (6), h_t is the final result of the model. Formula (6) can ensure the purity and clarity of the output signal by generating an enhanced speech signal. In the training process of LSTM, error backpropagation, and gradient descent are key steps to correct and optimize network weights. Error backpropagation can calculate the gradient of each parameter in the model. For LSTM, this process unfolds over time, calculating gradients at each past time step to ensure that the model can learn and adjust parameters to minimize errors. In speech enhancement models, this means that the model can gradually learn how to effectively filter noise and enhance speech signals. Gradient descent adjusts the parameters of the model based on the gradient information obtained from error backpropagation. By continuously iterating and updating parameters, the gradient descent algorithm gradually approaches the optimal solution, minimizing the error function of the model. The principle of error transmission can be found in formula (7) [12].

$$\delta_k^T = \prod_{j=k}^{t-1} \delta_{o,j}^T W_{oh} + \delta_{f,h}^T W_{fh} + \delta_{i,h}^T W_{ih} + \delta_{c,j}^T W_{ch}. \quad (7)$$

In formula (7), δ_k^T is the propagation error. The calculation of its gradient descent is determined based on the sum of the gradients of the "input gate", "forget gate" and "output gate" in the model at this moment. The weight gradient formulas of each gate are shown in formula (8).

$$\frac{\partial E}{\partial W_{ox}} = \delta_{o,t} x_t^T \quad \frac{\partial E}{\partial W_{ix}} = \delta_{i,t} x_t^T \quad \frac{\partial E}{\partial W_{fx}} = \delta_{f,t} x_t^T \quad \frac{\partial E}{\partial W_{cx}} = \delta_{\tilde{c},t} x_t^T \quad (8)$$

In formula (8), E is the loss function. Therefore, after obtaining the overall error, the network will perform the backpropagation step of the error. During this process, errors will be dispersed to various neural units based on existing weights and thresholds, and then the gradient descent strategy will be used to adjust the weights and perform forward propagation to generate outputs.

2.2 Construction of progressive language enhancement model based on LSTM

The LSTM-based speech signal enhancement model constructed above has significant advantages in dealing with long-term dependencies and noise filtering, but the model still has some shortcomings. For example, the computational complexity of the model is high, resource consumption is high, and gradients are prone to vanishing and exploding [13-15]. To address the limitations of the above model, this study introduces a progressive strategy into LSTM, with the main objective of enhancing speech signals layer by layer. Figure 3 shows the basic idea of progressive speech enhancement.

In Figure 3, the kernel of progressive speech enhancement starts with simple tasks and gradually learns and solves more complex problems. This method is particularly suitable for the task of converting noisy speech signals into clear speech. The specific implementation method is to decompose the entire problem into multiple small steps by increasing the SNR. Each small step focuses on improving the SNR of the input speech. Specifically, under low SNR conditions, the model first focuses on removing background noise, improving the basic structure of speech signals, and gradually enhancing the comprehensibility of signals at various stages. With the gradual improvement of SNR, the model can identify and enhance speech features more accurately in the subsequent processing stage, thereby achieving higher-quality speech signal output. This study introduces a progressive strategy into the speech enhancement model, and its structure is shown in Figure 4.

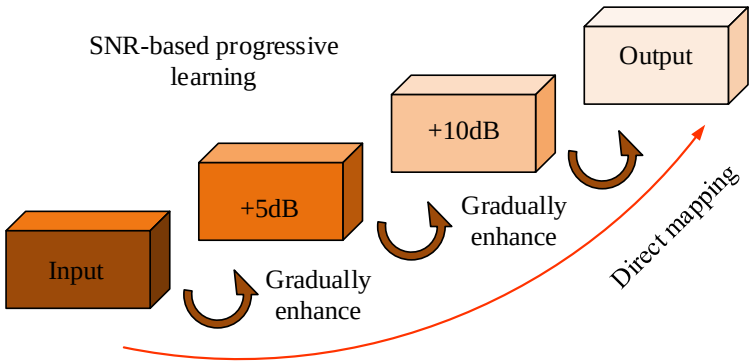

Figure 3 Basic Strategy Diagram of Progressive Speech Enhancement

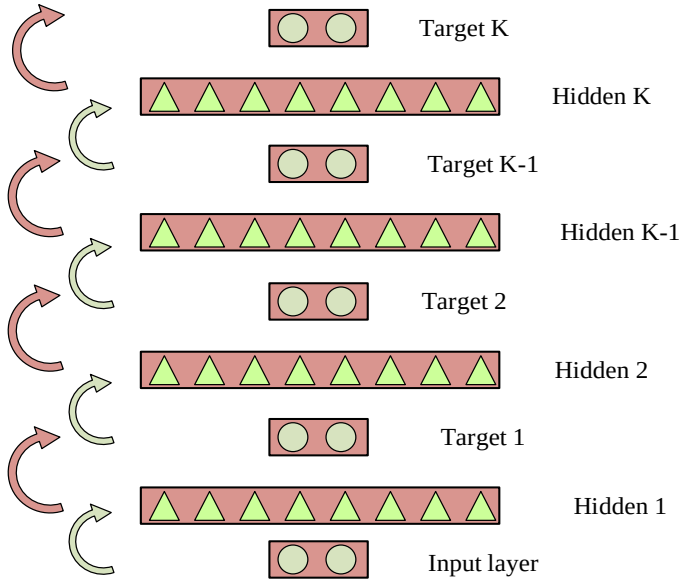

Figure 4: Speech enhancement structure based on progressive strategy

In Figure 4, the model achieves step-by-step optimization and enhancement of noisy speech signals through a multi-level and gradual enhancement method. The input layer receives noisy speech signals and performs preliminary preprocessing. The hidden layer extracts and processes speech features layer by layer, and enhances feature representation ability through nonlinear activation functions. The intermediate target layer learns an intermediate target with a higher SNR than the output of the last layer, gradually increasing the SNR. The target layer uses a linear activation function to generate the final enhanced speech signal. This study uses a weighted multi-objective learning objective function to train the network, as shown in formula (9) [16-17].

$$\begin{cases} e^{PL} = \sum_{k=1}^{K} \beta_k e_k^{PL} \\ e_k^{PL} = \frac{1}{U} \sum_{u=1}^{U} \left\| \mu_k^{PL}(\hat{x}_u^{k-1}, \Lambda_k^{PL}) - x_u^k \right\|_2^2 \end{cases} \tag{9}$$

In formula (9), e is the objective function. K represents the number of hidden layers. $\hat{x}$ denotes the estimated value of the target. x_u^k is the learning objective. U is the number of samples for network structure updates. β is the error weight coefficient. x_u^0 is a noisy speech feature. $\mu_k^{PL}(\hat{x}_u^{k-1}, \Lambda_k^{PL})$ is the target layer network function. Λ_k^{PL} is a paranoid vector.

In the above model structure, if the amount of intermediate target layers gradually increases, the performance of the model may be negatively affected. Meanwhile, the quality of effective information output by the model will decrease as the number of learning objectives increases. Therefore,

this study further adopts the DC approach to improve the model and obtained the LSTM-PLDC. Figure 5 shows the LSTM-PLDC model structure.

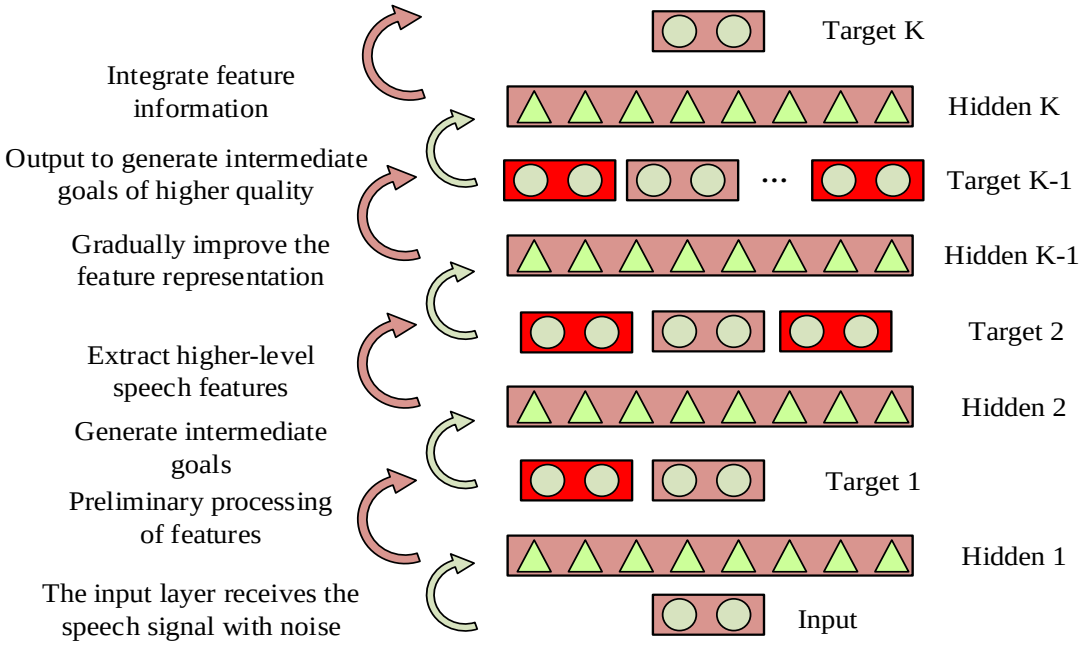

Figure 5: Speech enhancement structure based on LSTM-PLDC

In Figure 5, the design of the target layer aims to gradually optimize the SNR by combining the features output by the input layer and each intermediate layer. At each learning stage, the target layer extracts key information from the output of the previous layer and learns to generate intermediate targets with higher SNR. This mechanism enables the model to gradually improve the quality of speech signals in stages, making each target layer a performance measure and a key link in achieving effective information transmission and gradual enhancement, ultimately improving the clarity and comprehensibility of the overall speech signal. When learning intermediate targets, the model concatenates the original input and the estimated results of each target together, and then inputs them into a sub network. This method enables the sub network to simultaneously obtain the features of the initial noisy speech and the estimated features of speech with different SNRs. Due to the involvement of multiple learning objectives in DC's progressive learning, this study adopts a weighted Minimum Mean Square Error (MMSE) criterion as the objective function. The training and updating of the model are shown in formula (10).

$$\begin{cases} e^{PLD} = \sum_{k=1}^{K} \beta_k e_k^{PLD} \\ e_k^{PLD} = \frac{1}{U} \sum_{u=1}^{U} \left\| \mu_k^{PLD}(\hat{x}_u^0, \hat{x}_u^1, ..., \hat{x}_u^{k-1}, \Lambda_k^{PLD}) - x_u^k \right\|_2^2 \end{cases} \tag{10}$$

Formula (10) uses weighted MMSE criterion for multi-objective optimization to ensure that the model can effectively enhance speech signals under different SNR conditions. When the model processes different SNRs, speech distortion may occur due to excessive noise reduction. Other intermediate targets close to the target layer have lower SNR and can better preserve speech. This study uses formula (11) to solve the above phenomenon.

$$\hat{x}_n = \begin{cases} \dfrac{\hat{x}_u^K + \hat{x}_u^{K-1}}{2} & K = 2 \\ \dfrac{\hat{x}_u^K + \hat{x}_u^{K-1} + \hat{x}_u^{K-2}}{3} & K \geq 3 \end{cases} \tag{11}$$

By using formula (11), the model can learn speech features with different SNRs through multiple learning objectives, thereby better balancing denoising and speech feature preservation. The implementation process based on the LSTM-PLDC model proposed mainly includes the input layer receiving noisy speech signals and performing preliminary preprocessing operations for subsequent feature extraction. The hidden layer extracts and processes speech features layer by layer, and enhances feature representation ability through nonlinear activation functions. Each intermediate target layer learns an intermediate target with a higher SNR than the output of the previous layer, gradually increasing the SNR. By training and updating the model, the loss of each intermediate objective is calculated, and the total objective function is weighted and summed based on the weight

coefficients. According to the overall objective function, to backpropagate and update the model parameters to gradually optimize the model and achieve the best speech enhancement effect.

3 Results

3.1 Training analysis based on progressive language enhancement model

To verify the model's performance, the study adopts the TIMIT corpus for model training and testing. The TIMIT speech dataset has diverse speech samples and high-quality annotations, making it an ideal choice for evaluating speech enhancement effects. During the data preprocessing process, the audio file is first loaded and converted into a unified sampling rate. Then, the audio signal is subjected to frame segmentation and feature extraction, and the MEL frequency cepstral coefficient is adopted as the input feature. When simulating noise conditions in a real environment, various background noises are mixed with the target speech based on different SNRs. The processed data are divided into the training set, the validation set, and the test set to ensure the generalization ability of the model. Model training involves designing an architecture based on LSTM, combining dense connections and progressive learning mechanisms, using weighted MMES criterion as the loss function, and updating weights using Adam optimizer. During the training process, the early stop strategy is applied to prevent overfitting and ensure the performance optimization of the model on the validation set. 1660 sentences are randomly selected from the TIMIT corpus as the target speech, and the target speech is divided into training speech and validation speech in an 8:2 ratio. Then, the target speech is mixed with various types of noise based on different SNRs, including -5dB, 0dB, 5dB, and 10dB. The selection of mixed noise comes from five types of noise in noise -92 dB, including noisy noise, factory noise, spectral noise, vehicle noise, and horn noise. This study uses Perceived Evaluation of Speech Quality (PESQ), Short-Time Objective Intelligibility (STOI), Source-to-Distortion Ratio (SDR), and Word Error Rate (WER) as evaluation metrics for the model.

To ensure the optimal performance of the LSTM-PLDC model, a series of strategies are adopted in the selection and tuning process of hyperparameters. Firstly, the initial setting of the learning rate is 0.001, and the learning rate attenuation method is adopted during the training process. Specifically, every 10 training cycles (Epochs), the learning rate is reduced to 90% of the original to promote the model's convergence. The Dropout rate is set to 0.5. This is to effectively prevent the overfitting phenomenon of the model and ensure the generalization ability of the network by randomly discarding some neurons. The number of layers of the model is set to 6 LSTM units to balance the model depth and computational complexity, while maintaining a good capture ability for long-term dependencies. The batch size is selected as 64 to enable the effective utilization of diverse data in each iteration while ensuring the stability of the training process. The dense connection part adopts the "DenseNet" structure, which specifically connects the output features of each layer with the features of the previous layer, effectively enhancing information flow and feature reuse. The initialization method used is He initialization, which can effectively avoid the problems of gradient vanishing and explosion. In LSTM-PLDC, different learning objectives have a certain impact, as displayed in Figure 6.

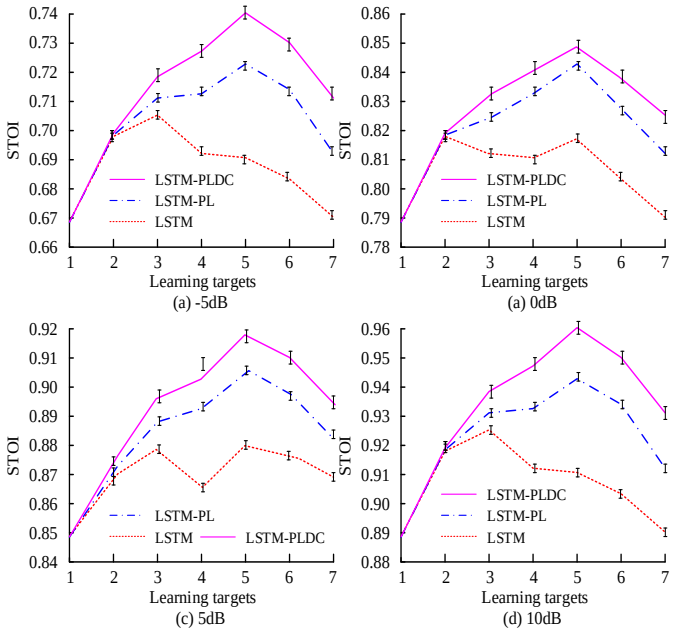

Figure 6: The impact of the number of target learning layers on the model

Figs. 6 (a) - (d) show the impact of the learning target layer on the model under SNR environments of -5dB, 0dB, 5dB, and 10dB. In Figure 6 (a), under the condition of -5dB, when the Learning target layer is 2, the differences among LSTM, Long Short-Term Memory-Progressive Learning (LSTM-PL), and LSTM-PLDC are relatively small. The STOI values of the three models are all around 0.715. When the learning objective layer gradually increases to 4, the STOI value of LSTM-PLDC reaches 0.740, the STOI value of LSTM-PL reaches 0.722, and the STOI value of LSTM is 0.693. In Figure 6 (b), under the condition of 0dB, the three algorithms achieve the best STOI value when the learning target layer is 5. Among them, the STOI value of LSTM-PLDC is 0.853, LSTM-PL is 0.846, and LSTM is 0.828. In Figure 6 (c), under the condition of 5db, the optimal STOI value for LSTM-PLDC is 0.918, LSTM-PL reaches 0.915, and LSTM is 0.903. In Figure 6 (d), the optimal STOI values under 10db conditions are 0.956 for LSTM-PLDC, 0.949 for LSTM-PL, and 0.948 for LSTM. This indicates that increasing the number of learning target layers can improve the short-term objective clarity of the model, and LSTM-PLDC exhibits the best clarity improvement effect under various SNR conditions. This also indicates that the LSTM-PLDC model has stronger robustness and higher speech quality when dealing with noisy speech. Similarly, the hidden layer structure of a model can also affect its performance. This study analyzes the number of different hidden layers and nodes, as shown in Figure 7.

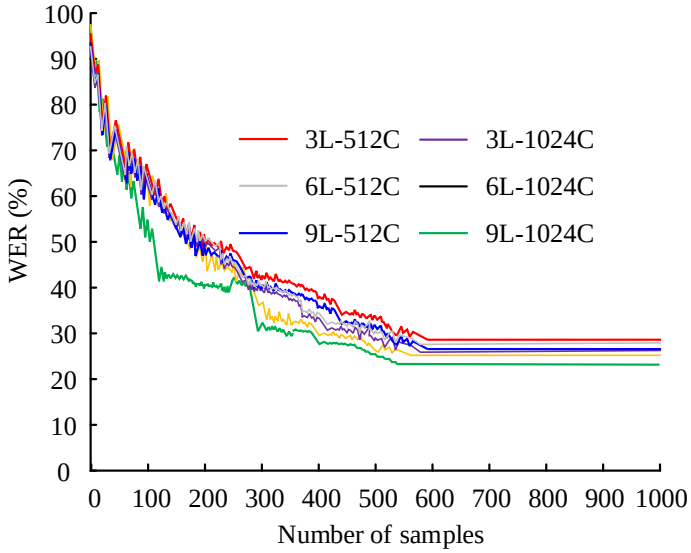

Figure 7: Performance impact of model structure

In Figure 7, the quantity of hidden layers is divided into 3, 6, and 9 layers, with 513 and 1024 nodes respectively. Under the same number of nodes and the same number of hidden layers, the higher the number of hidden layers and nodes, the lower the WER value of the model. Among them, when the number of hidden layers is 9 and the number of nodes is 1024, the WER of the model is about 24.82%. Compared to the model structure with 3 hidden layers and 513 nodes, its WER decreased by 3.09%. Figure 7 shows that increasing the number of hidden layers and nodes has a positive impact on model performance, and the combination of the two has a more significant effect. When designing a speech model, increasing the number of hidden layers and nodes appropriately can significantly improve the performance, reduce WER, and thus improve the accuracy of speech recognition. To further analyze the model's performance, this study trained different models on speech and obtained comparative results of the performance of different models, as shown in Table 2.

Table 2: Performance of models with different structures under training speech

Model structure	Model size (M)	WER (%)	Running time (s)
3L-512C	19.1	28.02	372
6L-512C	28.5	26.97	985
9L-512C	37.2	25.85	936
3L-1024C	46.3	25.88	948
6L-1024C	73.3	25.34	1769
9L-1024C	112.1	24.87	2051

In Table 2, the "L" in the model structure represents the number of hidden layers. "C" represents the number of nodes. When the hidden layers increase from 3 to 9, with 512 nodes, WER decreases from 28.02% to 25.85%, and runtime increases from 372 s to 936 s. Under 1,024 nodes, WER decreases from 25.88% to 24.87%, and runtime increases from 948 s to 2,051 s. When the nodes increase from 512 to 1024: under 3 hidden layers, the model size increases from 19.1 M to 46.3 M, and under 9 hidden layers, it increases from 37.2 M to 112.1 M. This indicates that increasing the number of hidden layers helps to reduce WER and improve model performance, but also increases computation time and resource requirements. To evaluate the impact of each model component on performance, an ablation study is conducted to compare three different models: standard LSTM, LSTM-PL, and LSTM-PLDC. The study evaluates the model through performance indicators (STOI, SDR and PESQ) under multiple SNR conditions, and the results are shown in Table 3.

Table 3: Ablation experiments of the model

Evaluation index	LSTM	LSTM-PL	LSTM-PLDC
-5dB STOI	0.678	0.811	0.930
0dB STOI	0.812	0.846	0.957
5dB STOI	0.885	0.915	0.979
10dB STOI	0.914	0.949	0.986
-5dB SDR	2.31	3.24	4.12
0dB SDR	5.14	6.88	8.67
5dB SDR	7.89	9.22	11.45
10dB SDR	10.67	13.24	14.81
-5dB PESQ	1.77	1.80	1.86
0dB PESQ	2.41	2.55	2.85
5dB PESQ	2.85	2.92	3.10
10dB PESQ	3.01	3.06	3.13

Table 3 presents the results of the ablation study, which highlights the performance enhancements achieved by integrating progressive learning and dense connection strategies into the model. From the standard LSTM model to LSTM-PL and ultimately to LSTM-PLDC, the evaluation metrics (STOI, SDR, and PESQ) show a clear improvement trend under all SNR conditions. For instance, in the -5dB SNR condition, STOI scores improves from 0.678 with the standard LSTM to 0.930 with the LSTM-PLDC model, indicating a significant enhancement in speech intelligibility. Similar trends are observed in SDR and PESQ scores, with LSTM-PLDC achieving a maximum SDR of 4.12 and a PESQ score of 1.86 under the same -5dB condition. These results underscore the importance of the added components in refining the model's ability to enhance speech quality and intelligibility in noisy environments, ultimately showing that each enhancement contributes substantially to overall performance.

3.2 Performance testing based on progressive language enhancement model

The research model obtains a good model structure in training speech, and now the performance of the model is analyzed by verifying the speech. This study uses Time-Delay Neural Network (TDNN) for comparative analysis [18]. Figure 8 shows the average STOI of each model on five types of noise in the test set.

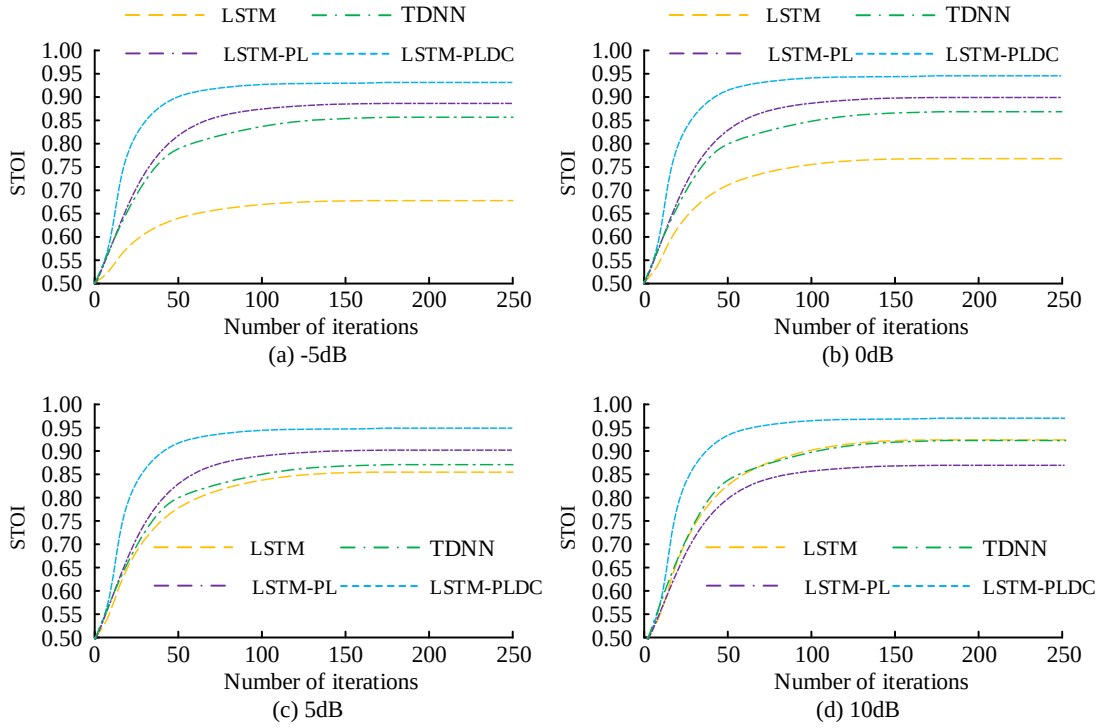

Figure 8: STOI results of each model in noise

Figs. 8 (a) -8 (d) show the average STOI values in SNR environments of -5dB, 0dB, 5dB, and 10dB. Regarding the results of the average STOI from -5dB to 10dB: LSTM increases from 0.678 to 0.930, LSTM-PL increases from 0.811 to 0.851, TDNN increases from 0.889 to 0.919, and LSTM-PLDC increases from -0.930 to 0.957. LSTM-PLDC has a 4.1% improvement compared to TDNN in the lowest SNR environment. Therefore, LSTM-PLDC has more effective noise suppression and speech enhancement effects in the model. Figure 9 shows the SDR of the model.

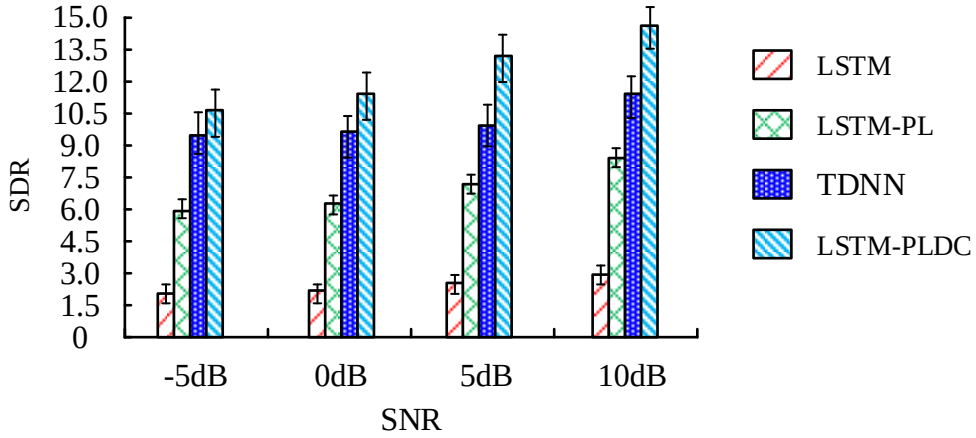

Figure 9: SDR results of four models in noise

Figure 9 shows the average SDR values in SNR environments of -5 dB, 0 dB, 5 dB, and 10 dB. The performance of LSTM gradually improves throughout the entire noise level range, from 2.31 at -5 dB to 10.67 at 10 dB. TDNN further increases the SDR value from 3.24 under low noise to 13.24 under high noise, indicating that TDNN may have specific advantages in extracting and preserving speech signals. LSTM-PLDC is 0.28 higher than TDNN, 1.57 higher at 10 dB, and has the highest SDR value at all noise levels. Overall, LSTM-PLDC still exhibits good performance in low SNR environments, indicating that the model has strong resistance to noise interference. Moreover, LSTM-PLDC can more accurately reconstruct speech signals and reduce noise components. Figure 10 shows the PESQ of each model on different types of noise in the test set.

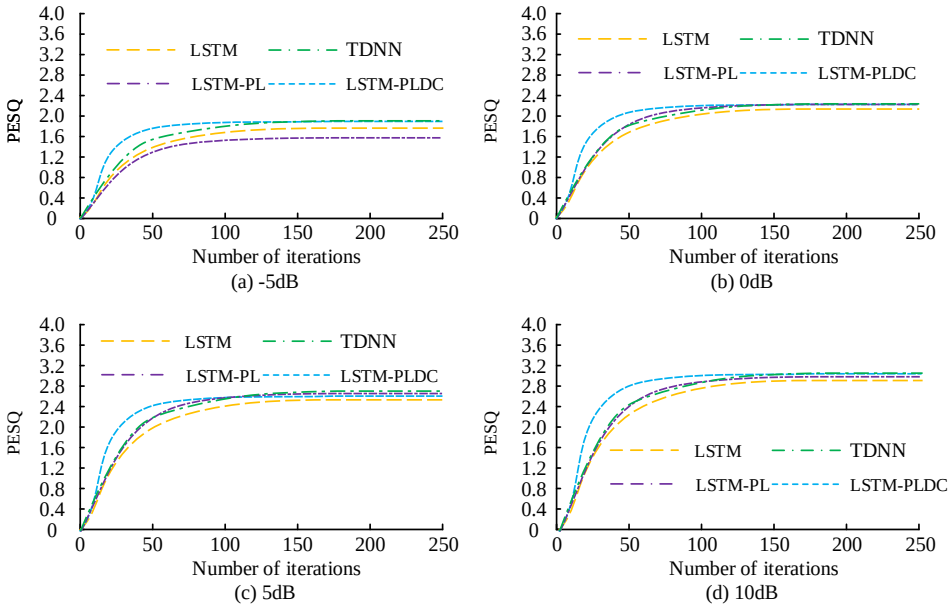

Figure 10: PESQ results of each model in noise

In Figure 10, the PESQ score increases from 1.77 to 3.01 in LSTM, from 1.70 to 3.06 in LSTM-PL, from 1.76 to 3.10 in TDNN, and from -1.86 to 3.13 in LSTM-PLDC in a noisy environment ranging from -5dB to 10dB. The performance of the LSTM-PLDC is superior to other models under -5dB noise conditions, indicating that the model effectively improves signal quality and reduces distortion. In the validation set, the WERs of each model are shown in Figure 11.

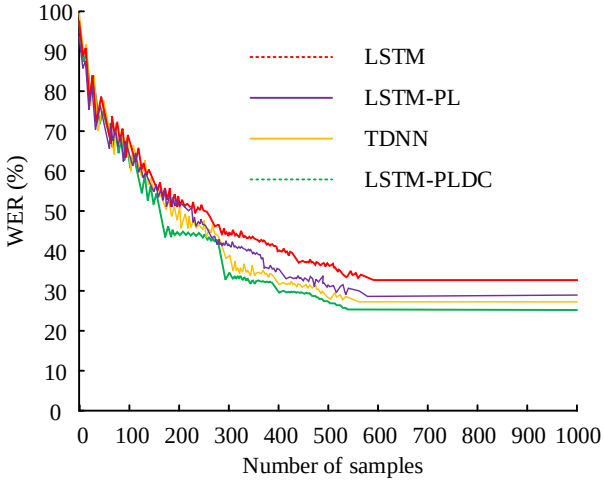

Figure 11: WERs of various models in the validation set

In Figure 11, the WER of LSTM is 36.45%, and that of the LSTM-PL is 30.33%. Compared to LSTM, LSTM-PL shows a significant decrease in WER, indicating that the progressive improvement method can effectively enhance speech enhancement performance. The WER of TDNN is 29.78%, while that of LSTM-PLDC is 27.31%. The WER of LSTM-PLDC further decreased by 3.02% compared to LSTM-PL, indicating that the progressive model using DC has better speech enhancement effect. Compared with TDNN model, LSTM-PLDC still has some advantages, which indicates that the improved model is feasible and progressiveness. To evaluate the robustness of the LSTM-PLDC model under real-world noise conditions, the study compares it with multiple baseline models to verify the model's validity. The noise datasets selected are CHiME and Aurora. Among them, the CHiME dataset is a noise dataset used for speech recognition, containing speech samples in different environments, such as homes, coffee shops, etc. The Aurora dataset is specifically designed to test the performance of speech recognition systems under various noise conditions, including different types of white noise and other environmental noises. The baseline models for comparison include Statistical Model-based Enhanced Noise Filtering (ENF), Wiener Filter (WF), DNN, Convolutional Neural Network (CNN), TDNN, and standard LSTM. The

experimental indicators adopted are STOI, SDR, PESQ, and MMSE. The performance comparison results of the model under real-world noise conditions are shown in Table 4.

Table 4: Performance verification of the model under real-world noise conditions

Model	LSTM	LSTM-PL	LSTM-PLDC	DNN	CNN	TDNN	WF	ENF
-5dB STOI	0.670	0.810	0.930	0.700	0.720	0.710	0.650	0.680
0dB STOI	0.790	0.826	0.950	0.783	0.795	0.810	0.760	0.775
5dB STOI	0.870	0.895	0.980	0.890	0.860	0.900	0.830	0.855
10dB STOI	0.900	0.940	0.990	0.910	0.880	0.920	0.850	0.880
-5dB SDR	2.100	3.100	4.120	2.550	2.800	2.650	1.900	2.200
0dB SDR	4.500	5.790	8.100	5.120	5.400	5.900	4.000	4.400
5dB SDR	6.810	8.100	11.300	7.670	8.000	8.200	6.200	7.300
10dB SDR	9.500	12.000	14.000	10.500	11.000	11.800	8.800	9.900
-5dB PESQ	1.700	1.800	1.870	1.750	1.760	1.790	1.600	1.730
0dB PESQ	2.200	2.400	2.900	2.300	2.340	2.360	2.100	2.250
5dB PESQ	2.600	2.850	3.100	2.750	2.800	2.880	2.500	2.700
10dB PESQ	2.850	3.010	3.120	3.000	3.050	3.020	2.700	2.950
-5dB MMSE	0.045	0.042	0.038	0.043	0.041	0.044	0.049	0.046
0dB MMSE	0.035	0.032	0.027	0.037	0.033	0.036	0.040	0.038
5dB MMSE	0.028	0.025	0.020	0.026	0.028	0.024	0.030	0.029
10dB MMSE	0.020	0.018	0.015	0.022	0.019	0.021	0.027	0.024

Table 4 presents the performance verification results of the LSTM-PLDC model under real-world noise conditions, with multiple baseline models for comparison. Under all the tested SNR conditions, the LSTM-PLDC model performs well in the STOI, SDR, and PESQ indicators. Especially under the condition of -5dB, its STOI reaches 0.930, and the result is higher than that of other models. Meanwhile, the SDR and PESQ scores of LSTM-PLDC are 4.120 and 1.870 under the condition of -5dB, both demonstrating superior noise reduction and speech quality performance. Compared with the traditional model, LSTM-PLDC reduces the MMSE value compared with other baseline models under all SNRs, indicating its higher accuracy in signal reconstruction. These results indicate that LSTM-PLDC has stronger robustness and effectiveness in adapting to real-world environmental noise, fully verifying its successful application in speech enhancement tasks. To enhance the statistical validation of the results, the study conducts a statistical significance test and clarifies the trade-off between model complexity and performance. The specific results are shown in Table 5.

Table 5: Trade-offs between model complexity and performance

Model structure	LSTM	LSTM-PL	LSTM-PLDC	DNN	TDNN
-5dB STOI	0.67	0.81	0.93	0.7	0.71
p value	/	0.003	<0.001	0.005	0.004
95% confidence interval (lower limit)	/	0.794	0.916	0.679	0.689
95% confidence interval (upper limit)	/	0.826	0.944	0.721	0.731
Number of hidden layers	2	4	6	3	5
Computational complexity (number of parameters)	1500	3000	5500	2200	4800
Performance improvement (%)	/	20.9	14.8	4.5	5.5

Table 5 shows the trade-off results of different model structures in terms of performance and complexity. Under the condition of a -5dB SNR, the STOI of the LSTM-PL model reaches 0.81, which is significantly increased by 20.9% compared with the standard LSTM, and its *p*-value is 0.003, indicating that this improvement is statistically significant. The LSTM-PLDC further increases the STOI to 0.93, and at the same time shows a *p*-value of <0.001. Moreover, the lower and upper limits of the confidence interval are 0.916 and 0.944, demonstrating the robustness of the model under noisy conditions. It is worth noting that the hidden layer number of LSTM-PLDC is 6 layers and the number of parameters reaches 5,500, showing a relatively high computational complexity. The number of parameters for DNN and TDNN models is 2200 and 4800, and the performance improvement is relatively limited. This result highlights the need for a balance between model complexity and performance. Although adding a hidden layer enhances the speech enhancement effect, it also brings higher demands for computing resources.

4 Discussion

The LSTM-PLDC model performed well in the speech signal enhancement task, especially with certain improvements in robustness and speech quality. The comparison with the relevant literature summary table clearly showed the advantages and disadvantages of the model. Firstly, in terms of STOI, the LSTM-PLDC model achieved 0.930 SNR at -5 dB, which was significantly higher than the result reported in Reference [6]. However, the STOI performance of the unsupervised learning method in Reference [7] under the same conditions was more limited. The main difference lies in the combination of progressive learning strategy and dense connection architecture in the LSTM-PLDC model, which effectively enhances the ability to extract useful features from speech signals and filters out background noise well. This design enables the model to maintain the clarity of speech in a high-noise background and has stronger adaptability in dynamic scenes, showing higher robustness compared to traditional methods. Furthermore, SDR is an important indicator for evaluating the effect of speech enhancement. In the experiments of the research, the SDR of the LSTM-PLDC model increased from 2.31 at -5 dB to 14.81 at 10 dB, which was superior to the relevant results in Reference [5]. This indicates that LSTM-PLDC performs outstandingly in the ability to effectively suppress noise and reconstruct clear signals. However, due to the characteristics of unsupervised learning, the method in Reference [7] may not be able to fully capture the signal uncertainty under certain noise conditions, resulting in the restoration effect not reaching the best. This result highlights the competitive advantage of LSTM-PLDC in complex noise environments. Priyanka S S et al. achieved speech enhancement through DNNs and CNNs. These models typically have a fixed feedforward structure and can also be trained to classify speech with different SNRs. LSTM-PLDC has the characteristics of progressive learning and dense connections, making it more suitable for sequential data and dynamically changing background noise [19]. Garg A optimized the structure of the LSTM model by using the attention mechanism and conducted speech recognition analysis on the optimized model, achieving certain results in the results [20]. However, compared with the LSTM-PLDC model, there is still a certain gap in its speech enhancement performance.

Although the LSTM-PLDC model performs well in multiple parameters, it also has some limitations at the same time. Firstly, due to its high model complexity, large computational resources, and high time overhead, its practical application is limited to a certain extent, especially under resource constraints. Although a higher number of hidden layers and nodes can reduce the power, it also brings a certain computational burden. Furthermore, although the model performs well in most noisy environments, it still faces challenges at extreme noise levels, such as extremely low SNRs or very complex noise backgrounds. This is because when the background noise intensity is too high, the model may encounter information loss, leading to difficulties in extracting and restoring speech features, thereby affecting the final enhancement effect.

5 Conclusion

In response to the limitations of traditional LSTM models in processing long time series speech signals, this study constructed a progressive language signal enhancement model based on LSTM and obtained the LSTM-PLDC model by introducing DC. Through comparative experiments, the proposed LSTM-PLDC had significant advantages in speech enhancement performance compared to LSTM, LSTM-PL, and TDNN. Experiments have shown that LSTM-PLDC had significant robustness in processing noisy speech in low SNR environments and could more accurately reconstruct speech signals, reducing the impact of noise interference. Although the LSTM-PLDC model has demonstrated superior speech enhancement performance in various noise environments, there are still some limitations. Firstly, the complexity of the model leads to a high demand for computing resources and training time, which may limit its application in a resource-constrained environment. Furthermore, although it performs well in most common noise environments, the robustness and generalization ability of the model still need to be further verified under extreme noise conditions or in the absence of noise types. Future research can focus on optimizing the model architecture to reduce computational complexity. Meanwhile, transfer learning and unsupervised learning techniques can be utilized to enhance the model's adaptability to new noisy environments. Furthermore, exploring the combination of context information and

higher-level audio feature extraction techniques may further enhance the speech enhancement effect and promote progress in this field.

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Process Parameter Optimization and Crack Density Prediction in Laser Cladding Using a BP Neural Network Model

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To address the crack defects arising from the complex nonlinear mapping relationship between key laser cladding process parameters and coating preparation, this study conducted a theoretical analysis and experimental verification by employing a BP neural network to predict crack density based on orthogonal experimental data. Initially, a three-factor four-level orthogonal experiment was performed to obtain fundamental sample data for the neural network, followed by dataset expansion using kernel density estimation (KDE). The dataset was then preprocessed through min-max normalization, ultimately establishing a three-layer predictive neural network model that correlates laser cladding layer process parameters (powder feeding rate, overlap rate, and scanning speed) with crack susceptibility. The results demonstrate that the BP neural network model achieves crack density predictions with relative errors fluctuating within ±5%, while maintaining an average error of 0.85% and a mean square error of 1.11%, indicating high prediction accuracy and stable performance. Furthermore, a comparative analysis of various regression methods, including KNN, Ridge, and Random Forest, was conducted in terms of R^2, RMSE, and MAE metrics, revealing that the BPNN exhibits superior comprehensive performance. These findings validate the feasibility of applying BP neural networks for crack density prediction through process parameters in laser cladding applications, which holds significant importance for fabricating crack-free nickel-based cladding layers.

Povzetek: Študija z ortogonalnimi eksperimenti in razširitvijo podatkov (KDE) vzpostavi BP-nevronski model, ki iz procesnih parametrov (dovod prahu, prekrivanje, hitrost skeniranja) napoveduje gostoto razpok pri laserskem navarjanju Ni60 ter podpira optimizacijo postopka glede na razpoke odporne obloge.

1 Introduction

With the continuous development of laser cladding technology, it has shown many advantages in the manufacturing of large and complex metal workpieces and metal surface strengthening processes [1]. Laser cladding is an advanced manufacturing method that uses high-energy laser beams to rapidly melt and solidify powder and substrate. However, due to the complex process of integrating multiple physical fields in laser cladding, the interaction between process parameters such as powder feeding rate, laser power, laser scanning speed, etc. will affect the quality of the deposited metal layer [2]. The coating is prone to serious cladding defects such as cracks [3], especially when cladding materials with higher hardness, which greatly limits the promotion, development, and application of laser cladding technology [4, 5]. Using traditional process experiments to control cracks is time-consuming, labor-intensive, and wasteful of resources, and the effect is average. How to comprehensively and intelligently control the factors that affect the cladding process is a hot research direction in this field [6, 7].

In this study, we investigated the challenge of crack formation in high-hardness nickel-based coatings by examining the key influencing factors of laser cladding crack generation and analyzing the feasibility of achieving crack density prediction errors below 10% using a three-layer BP neural network based on orthogonally designed input parameters. Previous research has demonstrated the application of BPNN in establishing mapping relationships between laser cladding parameters and coating characteristics, as summarized in Table 1. Ni and Liu from Central South University in Hunan Province optimized the melting process using neural networks and particle swarm optimization methods [8]; Huang et al. from Huazhong University of Science and Technology used neural networks to predict the characteristics and properties of aluminum alloy cladding layers [9]; Jiang et al. from the Shenyang Research Institute of the Chinese Academy of Sciences used neural networks to study the prediction of cladding height [10]; Yang et al. from Northwestern Polytechnical University used neural networks to predict

the morphology and quality of laser formed parts [11]; Lei et al. from Wuhan University of Technology studied the prediction of characteristic parameters of broadband laser cladding pool using neural networks [12]; Liu et al. from the School of Mechanical Engineering, Hubei University of Technology studied the prediction of the morphology of nickel based alloy overlay layer using GA-BP neural network [13]. However, it is not difficult to find that most scholars still mainly use BPNN to predict the height, width, morphology and other characteristics of the cladding layer, and lack comprehensive multi factor intelligent crack prediction research for higher hardness cladding layers.

Table 1: Comparison of model performance characteristics

Reference number	Model Name	Prediction Target	Model Mapping Relationship	Quantitative Result
7	BPNN+PSO	Characteristics of the cladding layer - height and width	The relationship between cladding bead characteristics (width, height) and cladding process parameters	Relative errors less than 4.5%
8	ANN	Prediction of characteristics and properties of aluminum alloy cladding layers	The relationship between laser cladding process parameters and the characteristics/properties of cladding layers	The maximum error value is 12.5%
9	BPNN	Prediction of clad height	The relationship between laser process parameters and clad height	Mean squared error of 0.0091
10	BPNN	Prediction of surface quality in formed components	The relationship between scanning speed and infill angle during laser additive manufacturing and the surface quality evaluation parameters of fabricated components	MSE < 0.01
11	GA-BP	Prediction of coating morphology	The mapping relationship between laser processing parameters and the macroscopic morphology of cladding layers	Average relative error of 3.951%
12	BPNN	Prediction of melt pool characteristics in wide-band laser cladding	The relationship between laser cladding process parameters (laser power, powder thickness, scanning speed) and melt pool characteristic parameters	Errors less than 2% and correlation coefficient R approaching 1

Therefore, from the perspective of crack sensitivity analysis, in order to better meet the quality requirements of the cladding layer, the mechanism of crack formation was theoretically analyzed, and the cladding parameters were determined to be important factors leading to crack formation. Through the Analytic Hierarchy Process (AHP), it was clarified that process parameters such as powder feeding rate, overlap rate, and scanning speed had the greatest impact on crack sensitivity. Then, by designing a 3-factor 4-level orthogonal experiment, sample data of crack density was collected. Based on the data provided by the orthogonal experiment, the data was expanded through

interpolation, and a neural network model was constructed with the processed sample data as a reference, achieving a nonlinear mapping relationship between various process parameters and crack density.

The contribution of this article is to propose a neural network prediction model based on small sample data on the basis of a small number of experiments. It can accurately predict crack density through process parameters such as powder feeding rate, overlap rate, and scanning rate. This can reduce the amount of process experiments, save materials, and analyze the impact of uncertain nonlinear factors on cracks in laser cladding layers with high hardness. At the same time, it provides a feasible new approach to reduce the number of offline experiments and prepare crack free coatings.

2 Experimental materials and methods

2.1 Experimental materials

Through the study of coating cracks, 45# steel was selected as the substrate, with a substrate size of 110 mm×60 mm×6 mm and a quantity of 16 pieces. In order to minimize the effect of external factors on the cladding layer, the steel plate was polished and polished before using the 45# steel substrate. Then, the surface of the steel plate to be clad was cleaned with anhydrous ethanol to ensure that the substrate surface was flat and free of rust, oil, and other impurities. Ni60 powder is selected as the laser cladding powder, with a powder size of 140-325 mesh. Due to the fine powder, it is prone to moisture absorption and agglomeration in the air, which affects the experimental results. Therefore, it is necessary to dry and remove the powder before use. The element content in the 45-steel matrix is shown in Table 2, and the element content in the Ni60 self-melting laser cladding powder is shown in Table 3.

Table 2: Contents of elements in 45# steel (w%)

Element	Cr	Si	C	Mn	Ni	Cu	Fe
45 # steel quality score	≤0.25	0.17-0.40	0.42-0.50	0.50-0.80	≤0.25	≤ 0.30	Balance

Table 3: Content of elements in Ni60 self-melting powder (w%)

Element	C	Cr	B	Si	Fe	Ni
Ni60 quality score	0.7-1.0	14.0-17.0	3.0-4.5	3.5-5.5	≤15.0	Margin

2.2 Experimental equipment and methods

The German KUKA machine KR30HA was used in the experiment; Experimental research was conducted on the Xinsong XSL-PF-01B-2 synchronous side powder feeder; The protective gas used in the experiment is argon gas; The cooling system uses a dual temperature chiller unit, model PH-LW296-TH2P; The fusion equipment is undergoing testing as shown in Figure 1.

Figure 1: Experimental equipment

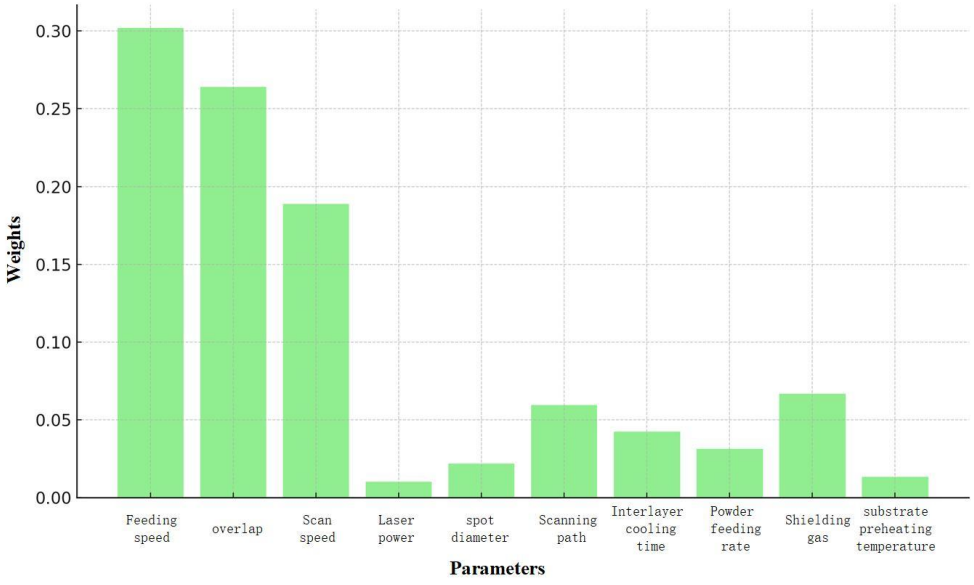


Figure 2: Results of the analytic hierarchy process (AHP) analysis

In general, process parameters such as spot diameter, scanning path, interlayer cooling time, powder feeding rate, protective gas, substrate preheating temperature, laser power, powder feeding speed, overlap rate, and scanning speed all affect the performance and morphology of coatings. The weight of process parameters such as spot diameter and scanning path to crack density was calculated using the Analytic Hierarchy Process (AHP), and the results are shown in Figure 2. Among them, the three process parameter variables of powder feeding speed, overlap rate, and scanning speed have the highest weight proportion to the results.

Meanwhile, the correlation analysis method was used to compare the correlation sensitivity between different parameters. As shown in Figure 3, the three process parameters of powder feeding speed, overlap rate, and scanning speed have the highest correlation with each other. In summary, the three parameters that have the greatest impact on coating performance and morphology and have a high correlation with each other, namely

powder feeding speed, overlap rate, and scanning rate, were selected as variables for the cladding experiment.

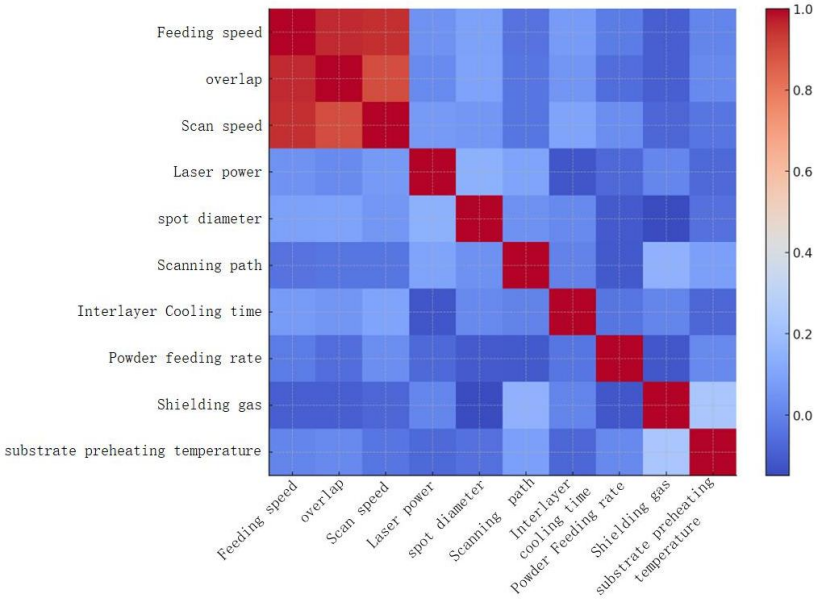
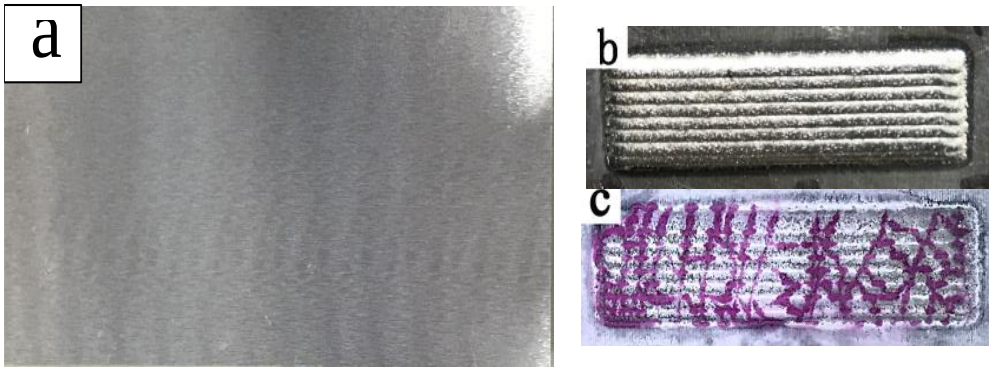


Figure 3: Results of correlation analysis

Due to the hardness of Ni60 powder, in the fusion process, only the powder feeding amount is changed. If other parameters remain unchanged, the total output energy of the laser remains unchanged. If the powder feeding amount is too large, most of the heat source is absorbed by the powder, and the heat reaching the substrate is relatively small. The temperature difference between the substrate and the fusion layer is large, and it rapidly cools at room temperature, resulting in an increase in crack generation; The powder feeding amount is too small, and the thickness of the cladding layer is thin. Due to the high energy of the laser delivered to the substrate, sintering may occur, and the thin cladding layer cannot achieve the purpose of laser repair. If there are multiple overlapping layers and other process parameters remain constant, excessive overlapping rate will result in over overlapping phenomenon. As the number of overlapping times increases, the cladding layer will gradually become thicker, and the surface of the cladding layer will tilt at a certain angle. The temperature gradient between the substrate and the cladding layer will gradually increase. If the overlapping rate is too low, it will lead to excessive surface ripples. Controlling the scanning speed of a single variable, under certain conditions, the crack sensitivity increases with the increase of scanning speed. Due to the fast-scanning speed, there is less heat input on the substrate, making it difficult for the substrate to form a fully melted melt pool with the powder, resulting in an increase in crack sensitivity [14].

Orthogonal experiments have two distinct characteristics, one is average dispersion, and the other is homogeneity and comparability. The so-called average dispersion refers to the equal occurrence of factor levels in each column; The so-called neat comparability refers to any pair of equivalent numbers in any two columns as a logarithm, where all possible pairs have the same number of repetitions. Based on the three variables of powder feeding speed, overlap rate, and scanning rate, a three factor four level orthogonal experiment L_{16} (4^3) was designed. The range of process parameters is shown in Table 4. The fusion experiment was conducted using a fusion robot, and each sample was subjected to 8 overlapping fusion layers. Then, non-destructive crack detection was performed using dye penetrant testing agent to measure and calculate the total length of cracks and the area of the fusion layer of each sample. The crack density was calculated by dividing the two, and to eliminate accidental errors and ensure data accuracy, the final crack density was determined by taking the average of multiple measurements. The experimental process of feeding 20 (g/min) powder, overlapping 50%, and scanning rate 10 (mm/s) is shown in Figure 4.



a-matrix; b-Laser cladding results; c-Nondestructive testing results

Figure 4: Test process

Table 4: Orthogonal experimental parameters

Level	Factor		
	powder feeding amount / (g/min)	lap rate / (%	scanning rate / (mm/s)
1	16	45	4
2	18	50	6
3	20	55	8
4	22	60	10

3 Establishment of neural network model and evaluation of simulation performance

3.1 Dataset construction

The results of the orthogonal experiments for laser cladding parameters are presented in Table 5. These representative experimental datasets will serve as training and testing samples for the neural network to predict crack density.

Table 5: Results of the laser cladding orthogonal test cladding

Test number	Powder delivery quantity/ (g/min)	overlapping ratio/ （%）	scan rate/ (*mm*/s)	crack density/（mm/mm^2）
1	16	45	4	0.201472
2	16	50	6	0.312450
3	16	55	8	0.331451
4	16	60	10	0.340142
5	18	45	6	0.234483
6	18	50	4	0.321578
7	18	55	10	0.369252
8	18	60	8	0.426565
9	20	45	8	0.275027
10	20	50	10	0.349855
11	20	55	4	0.352161
12	20	60	6	0.450340
13	22	45	10	0.290522

14	22	50	8	0.334810
15	22	55	6	0.371483
16	22	60	4	0.478756

However, due to the small amount of data obtained from orthogonal experiments, it may affect the learning results of the BP neural network and lead to underfitting. Therefore, based on single crack density values and historical experience values, kernel density estimation (KDE) is used to approximate uniform interpolation, thereby expanding the dataset.

Kernel Density Estimation (KDE) is a non parametric probability density estimation method that can fit distributions based on the characteristics and properties of the data itself, without making any distribution assumptions. For a sample set $\{x_1, x_2, \cdots, x_n\}$ consisting of n observations of a continuous random variable X, the KED method estimates the probability density function (PDF) of the random variable X using equation (1), denoted as $p(x)$.

$$\hat{p}(x) = \frac{1}{nh}\sum_{i-1}^{n} K(\frac{x - x_i}{h}) \quad (1)$$

where $\hat{p}(x)$ represents the estimated PDF, h denotes the bandwidth parameter of KDE, and $K(u)$ is the kernel function. Given n observations of a random variable X, if k values fall within the interval $[a, b]$, then $p(x)$ can be expressed as equation (2):

$$\hat{p}(x) = \frac{k}{n(b-a)} \quad (2)$$

By using a fixed interval $[a, b]$ and changing the size of k to estimate the PDF, the number of observations k among the n observations of the random variable X that fall within the interval $[a, b]$ can be expressed as equation (3):

$$k = \sum_{i-1}^{n} K(\frac{x - x_i}{h}) \quad (3)$$

Taking sample #1 as an example, its measurement results are presented in Table 6.

Table 6: Statistical summary of measurement results for test sample #1

Cladding bead	1 bead	2 bead	3 bead	4 bead	
Crack density /（mm/mm^2)	0.201683	0.104472	0.233796	0.211206	Average 0.201472
Cladding bead	5 bead	6 bead	7 bead	8 bead	
Crack density /（mm/mm^2)	0.1617654	0.325267	0.201031	0.172556	

The crack densities of eight individual cladding beads were treated as a sample set {0.104472, 0.1617654, 0.172556, 0.201031, 0.201683, 0.211206, 0.233796, 0.325267}. Using KDE with the Gaussian kernel function, we estimated the probability density function *p(x)* over the fixed interval defined by the minimum and maximum values [0.104472, 0.325267]. Uniform interpolation was then performed based on the derived PDF, with results presented in Table 7. The results from each orthogonal experiment can be expanded to 32 data values. Through this expansion process, the 16 sets of orthogonal experimental results yield a total of 512 data samples.

Table 7: Interpolation results of measurement data for test sample #1

Crack density	Crack density	Crack density	Crack density
0.104472	0.172556	0.201683	0.22476
0.11879535	0.179675	0.203588	0.229278
0.1331187	0.186794	0.205492	0.233796
0.14744205	0.193912	0.207397	0.25209

0.1617654	0.201031	0.209301	0.270384
0.16446305	0.201194	0.211206	0.288679
0.1671607	0.201357	0.215724	0.306973
0.16985835	0.20152	0.220242	0.325267

3.2 Establishment of neural network model

BP neural network has strong nonlinear mapping ability, fault tolerance, self-learning and adaptive ability, and has been widely used in engineering prediction. For the analysis of process data, an orthogonal experimental scheme was used to melt the Ni60 cladding layer as a sample for the BP neural network. The experimental results were compared with the predicted values of the neural network for performance evaluation. The neural network algorithm flow is shown in Figure 5.

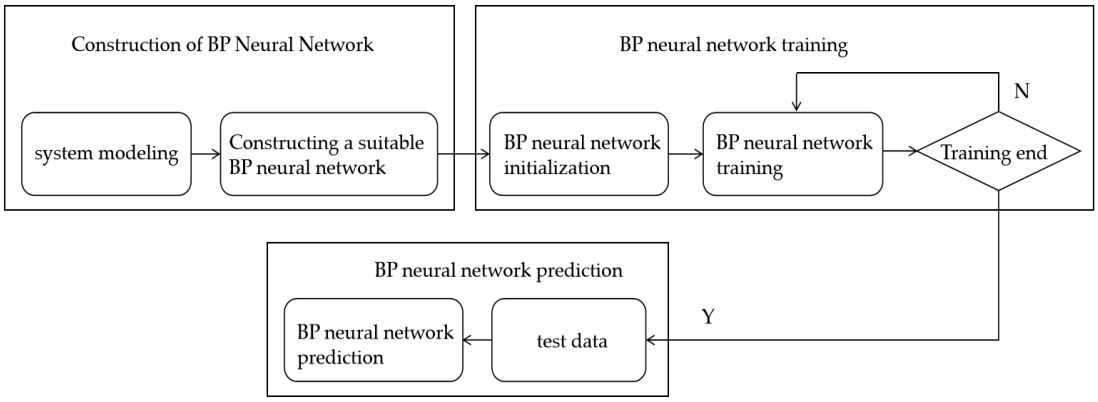


Figure 5: Algorithm flow

A three-layer predictive neural network structure model was established between the process parameters of laser cladding layer and crack sensitivity, as shown in Figure 6. The input layer has three neurons, namely powder feeding rate, overlap rate, and scanning speed, while the output layer only has one neuron, which is crack density. The number of neurons in the hidden layer can be calculated by empirical formula (4).

$$m = \sqrt{A + B} + C \tag{4}$$

In the formulation, A denotes the number of output neurons, B represents the number of input neurons, and C is an empirical constant.

The optimal number of hidden neurons was determined as 9 (search range: {4, 9, 16, 32}) through a combined grid search and Bayesian optimization approach, calculated based on input neuron count B and empirical constant $C \grave{o} [1,10]$, achieving minimal error on the validation set. The network architecture employs ReLU activation for the input layer to ensure computational efficiency, Swish activation in hidden layers to better model nonlinear relationships among process parameters, and linear activation for the output layer to meet regression requirements. To prevent overfitting, the model incorporates L_2 regularization (λ = 0.01) and a Dropout strategy (rate = 0.3). For the small-scale process data characteristics, the Adam optimizer (learning rate = 0.001, β_1 = 0.9, β_2 = 0.999) was selected to ensure training stability and convergence efficiency.

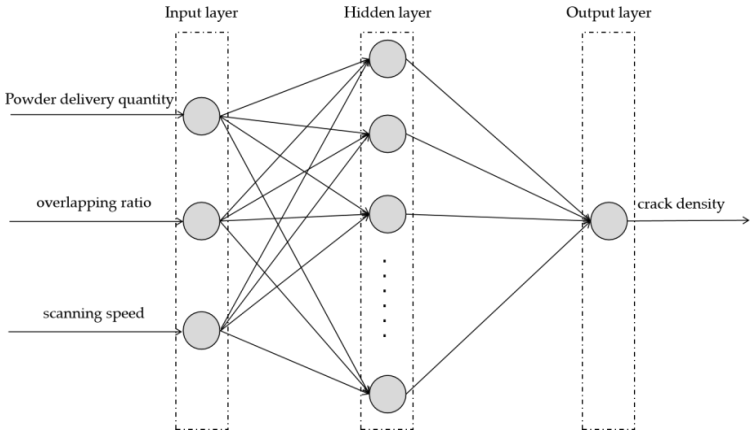


Figure 6: Prediction neural network structure model

3.3 Training and simulation of neural network models

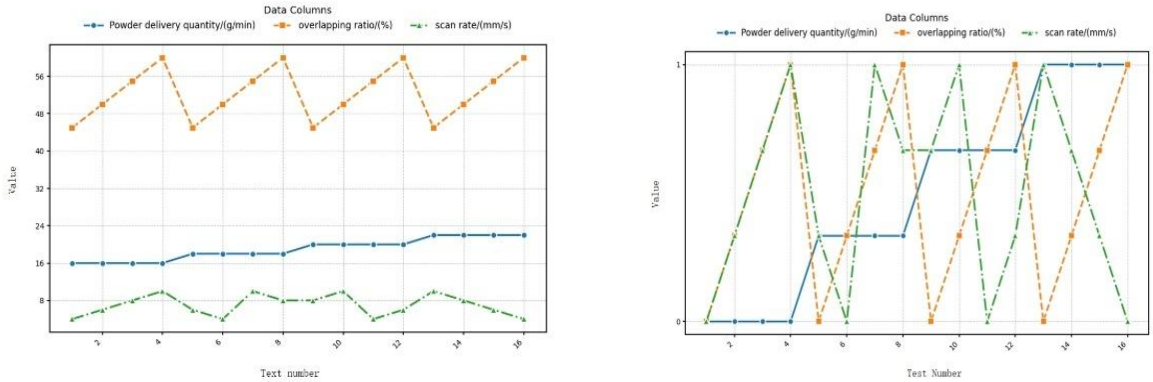
Selecting a certain range of powder feeding amount, overlap rate, and scanning speed as input values during the cladding process to use BP neural network to predict the density of cracks in the cladding layer can effectively control the amount of crack generation. Randomly divide the expanded dataset into a training set and a testing set according to an 8:2 ratio.

Due to the inconsistent units between various factors and output quantities in orthogonal experiments, it may lead to accuracy errors. Some neural networks have large data volumes, slow convergence, and long training times. In addition, the range of the activation function in their output layer is limited. Therefore, it is necessary to map the training target data to the range of the activation function, which requires data normalization. Substitute the three changing parameters and output training values into formula (5), and use the Min Max normalization method to convert the input training value test value and output training value into the range of [0,1].

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

Where, y represents the processed quantity, x is a single sample, x_{max} , x_{min} and represents the maximum and minimum samples.

As shown in Figure 7, the comparative variation of process parameters before and after normalization is illustrated, with aggregated statistics summarized in Table 8.



a) Process parameters before normalization b) Normalized process parameters

Figure 7: Process parameters before and after normalization

Table 8: Mean values and standard deviations of normalized process parameters

Process parameters	Average		Standard deviation	
	Before normalization	After normalization	Before normalization	After normalization
Powder feeding	19	0.5	2.309401077	0.384900256

amount				
Lap rate	52.5	0.5	5.773502692	0.384900256
Scanning rate	7	0.5	2.309401077	0.384900256

The model parameters were configured with 1000 maximum iterations and a training target of 1×10^{-6} at a learning rate of 0.01. In practice, the training error dropped below 10^{-6} and stabilized within 150 iterations, meeting the specified accuracy requirements. The convergence process of the iterative training loss is demonstrated in Figure 8.

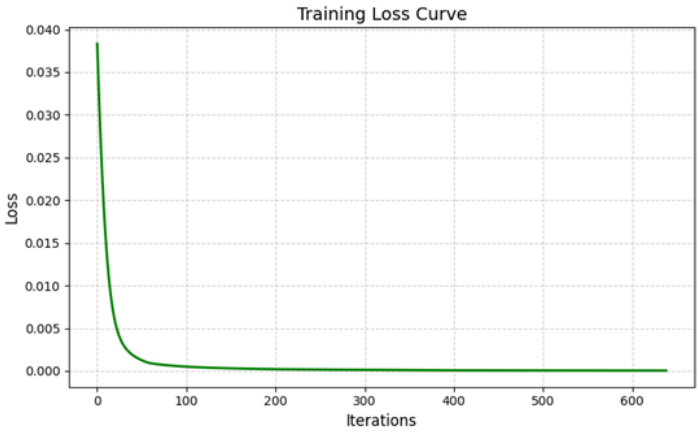


Figure 8: Training loss convergence process

3.4 Performance evaluation of the neural network model

The predictive model's accuracy was comprehensively evaluated using Equations (6)-(9) to calculate four key metrics: relative error (E), mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2). This multi-metric assessment framework provides rigorous validation of the model's reliability in predicting crack density.

$$E_i = \frac{|y_i - \hat{y}_i|}{y_i} \times 100\% \tag{6}$$

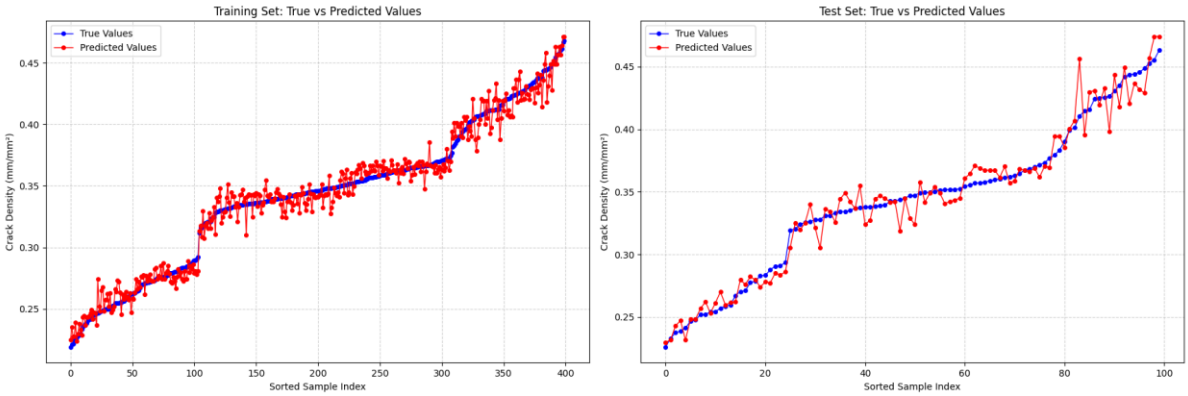
$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \in [0, +\infty) \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

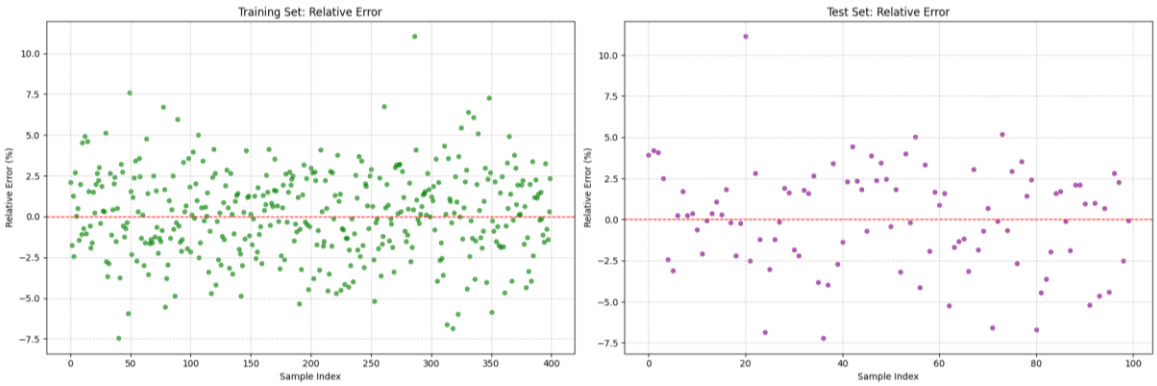
$$R^2 = \frac{[l\sum_{i=1}^{l}\hat{y}_i y_i - \sum_{i=1}^{l}\hat{y}_i \sum_{i=1}^{l} y_i]^2}{[l\sum_{i=1}^{l}\hat{y}_i^{\,2} - (\sum_{i=1}^{l}\hat{y}_i)^2][l\sum_{i=1}^{l} y_i^2 - (\sum_{i=1}^{l} y_i)^2]} \tag{9}$$

In the above formula, $\hat{y}_i(i=1,2,...,n)$ represents the predicted value of the i-th sample, while $y_i(i=1,2,...,n)$ denotes the corresponding true value. For the relative error E, smaller values indicate closer proximity to the true values and better model performance. The Mean Absolute Error (MAE) measures the average absolute deviation between predicted and true values as a non-negative metric, where smaller MAE values correspond to superior models. The Root Mean Square Error (RMSE), a key regression metric, quantifies the magnitude of prediction errors, assigning higher weights to larger errors; like MAE, smaller values are preferable. The coefficient of determination (R^2) ranges within [0,1], with values closer to 1 indicating better model performance and vice versa.

Figure 9 presents the training and prediction results of the BPNN model. As shown in (a) and (b), the model successfully captures the primary fluctuation trends in both the training and test datasets. Notably, the predicted values on the test set demonstrate closer alignment with the true values compared to the training set. The reduced sample size of the test set results in less complex data fluctuations relative to the training set. Panels (c) and (d) display the model's relative errors, which predominantly fluctuate within ±10%, indicating minimal errors for most samples. Remarkably, the test set's relative errors are further constrained within ±5%, demonstrating the model's reliability and high predictive accuracy for crack density estimation.



a) the true and predicted values of the training set b) the true and predicted values of the test set



c) corresponding relative errors of the training set d) corresponding relative errors of the test set

Figure 9: Training and prediction results of BPNN for crack density

As evident from Figure 10, the residuals are predominantly concentrated within ±0.01, indicating the model maintains excellent fitting capability with consistent stability.

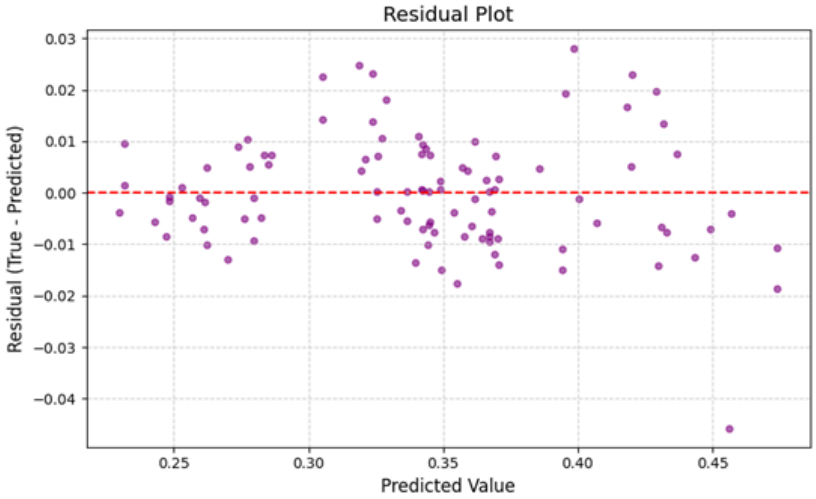


Figure 10: Residual plot of prediction samples

As shown in Table 9, the model's MAE, RMSE, and R^2 scores are presented. On the training set, the model achieves an R^2 of 0.9772, while on the test set, the R^2 is 0.9644, demonstrating strong fitting capability to the training data and reliable prediction of crack density in Ni60 self-fluxing alloy powder laser cladding layers within an acceptable error margin. Furthermore, the training set shows MAE and RMSE values of 0.0071 and

0.0089, respectively, compared to 0.0085 (MAE) and 0.0111 (RMSE) for the test set. The minimal discrepancy between these metrics indicates robust predictive performance in practical applications, with maintained effectiveness on random data samples.

Table 9: Performance metrics (R^2, MAE, RMSE) for training and test sets

	Coefficient of determination R^2	mean absolute error （MAE)	root mean square error （RMSE)
Training set	0.9772	0.0071	0.0089
Test set	0.9644	0.0085	0.0111

3.5 Comparative analysis with alternative models

Based on the aforementioned analysis, we evaluated multiple machine learning algorithms-including KNN regression, Ridge regression, XGBoost regression, AdaBoost regression, CatBoost regression, Random Forest regression, LSTM regression, BiLSTM-AdaBoost regression, and CNN regression-on the same dataset and compared their performance with BPNN regression. The R^2, MAE, and RMSE values for each model are summarized in Table 10.

Table 10: Comparative results of crack density prediction on the test set

Model name	R^2	MAE	RMSE
KNN	0.95002	0.00017	0.01301
ridge regression	0.88528	0.00039	0.01971
XGboost regression	0.92974	0.00024	0.01543
ADA boost	0.92604	0.00025	0.01583
Catboost	0.94618	0.00018	0.01543
Random forest	0.93593	0.00022	0.01472
LSTM	0.90605	0.01293	0.01784
BiLSTM-AdaBoost	0.91265	0.01313	0.01720
CNN	0.94571	0.00819	0.01356
BP Neural Network	0.96445	0.01109	0.00853

4 Discussion

The relationship between process parameters and crack susceptibility in laser cladding involves complex nonlinear interactions. The Backpropagation Neural Network (BPNN) was selected for this study to model the mapping between three key process parameters (powder feed rate, overlap ratio, and scanning speed) and crack density, owing to its exceptional nonlinear fitting capability and adaptive feature learning through error backpropagation that continuously optimizes network weights and thresholds to achieve high-precision modeling. Given the high cost and time-consuming nature of laser cladding experiments, orthogonal experimental designs are typically employed to investigate parameter-crack density relationships. However, neural networks like BPNN require substantial training samples for effective learning, which was addressed in this study through Kernel Density Estimation (KDE)-based data augmentation. Experimental results (Tables 9-10) demonstrate that the BPNN prediction model achieves test set errors within ±5%, with MAE and RMSE values of 0.85% and 1.11% respectively. Comparative analysis with KNN regression, ridge regression, XGBoost regression, AdaBoost regression, CatBoost regression, random forest regression, LSTM regression, BiLSTM-AdaBoost regression, and CNN regression confirms BPNN's superior performance, evidenced by its highest R^2 score of 0.96445. This superiority stems from BPNN's three-layer architecture employing nonlinear activation functions (ReLU/Swish) that effectively approximate the complex multi-parameter interactions in laser cladding crack prediction scenarios.

The proposed method effectively addresses the critical challenges of process parameter optimization and crack density prediction in laser cladding, demonstrating significant value for fabricating high-quality nickel-based cladding layers. Furthermore, this research offers valuable insights for cladding processes involving similar materials (titanium alloys or other superalloys). By

establishing a BPNN-based mapping between process parameters and target performance characteristics, the study provides a universal research paradigm for precise "process-performance" regulation in additive manufacturing, particularly enhancing process development efficiency for high-cost, high-precision manufacturing scenarios. Although this study has achieved significant results, there are still some potential limitations. The proposed method in this research lacks sufficient real-time optimization capability and an online learning mechanism, which hinders the model's self-adaptive iterative optimization ability in practical production environments. In future research, it will be essential to investigate elastic network structures with incremental learning capabilities and integrate online sequential learning algorithms to enhance the model's generalization ability and adaptability in engineering applications.

5 Conclusion

This study focuses on the laser cladding of Ni60 powder on 45# steel surfaces. By employing orthogonal experimental design combined with BP neural network modeling, we systematically investigated the nonlinear mapping relationship between process parameters (such as laser power, scanning speed, and powder feed rate) and crack density in the cladding layer. Through network training, learning, and predictive fitting, the reliability of the model was verified, providing a feasible solution for preparing crack-free nickel-based cladding layers. The results demonstrate that the BP neural network-based prediction model exhibits strong generalization performance on the test set, with a coefficient of determination (R^2) of 0.9644, indicating excellent fitting capability. Additionally, the mean absolute error (MAE) and root mean square error (RMSE) were 0.0085 and 0.0111, respectively, confirming the model's predictive stability.

Through comparative analysis with various other regression algorithms-including KNN regression, ridge regression, XGBoost regression, AdaBoost regression, CatBoost regression, random forest regression, LSTM regression, BiLSTM-AdaBoost regression, and CNN regression-the BPNN (Backpropagation Neural Network) model demonstrated superior stability and accuracy. This finding validates the feasibility of integrating theoretical modeling with experimental validation, offering a promising new approach for preparing crack-free nickel-based cladding layers.

Further analysis indicates that conventional backpropagation (BP) neural networks exhibit limitations in processing high-dimensional parameter interactions, manifesting as slow convergence rates and susceptibility to local optima. Moreover, the model necessitates complete retraining when applied to new alloy powder systems. To enhance the predictive accuracy of the network model, subsequent research could employ convolutional neural networks (CNNs) to extract morphological features from cladding layer images for improved parameter correlation modeling, while exploring Vision Transformer (ViT) architectures to integrate multimodal data, combining process parameters with molten pool dynamic monitoring images. Additionally, an online learning system could be implemented to enable dynamic closed-loop control of process parameters through real-time acquisition of spectral signals and thermal imaging data during the cladding process.

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Privacy-Preserving Multiclass Lung Disorder Classification via CNN with Cosine Similarity in Big Data Framework

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Keywords: big data, lung diseases, computed tomography scans, privacy-preserving, deep learning, image classification

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Annotating large-scale medical data manually takes a lot of time and human resources, and it requires specific medical knowledge and experience. Big data and Deep learning are two advancing technologies being widely used in the medical field for improved analysis. Because of the recent advancements in imaging technology, computer vision researchers still have unsolved problems related to automatically identifying medical images. Images, however, could include sensitive information about specific body parts and specifics of diseases. In actuality, sharing medical images that contain extremely sensitive information for each user may expose sensitive information to adversaries. One of the main issues between a user and a databank is privacy, we present in this study a Multi-layered convolutional neural network (MLCNN) integrated with PPCS (Privacy preserved cosine similarity) for feature extraction from large-scale medical image data. The framework that uses fully homomorphic encryption (FHE), CSSK(Cheon-Kim-Kim-Song) scheme to search for safe and to enable the categorization CNN is used for large-scale encrypted images. This study aims to diagnose various lung disorders such as COVID-19, lung cancer, pulmonary tuberculosis, pneumonia, and differentiate them from normal conditions by analyzing computed tomography (CT) images. The model's results included 98.54% F1 score, 97.11% Matthew's correlation coefficient (MCC), 98.89% accuracy (AC), 98.38% recall, and 98.81% precision (PC). We compare and contrast our privacy-preserving method with a CNN-based multiclass classification model that offers quick and effective classification.

Povzetek: Članek predstavi zasebnostno varno večrazredno klasifikacijo pljučnih bolezni iz CT posnetkov z MLCNN in PPCS (kosinusna podobnost) na velikih podatkih (Spark) s FHE/CKKS.

1 Introduction

As data is gathered by devices such as mobile phones, inexpensive and widely used information-sensing Internet of things (IOT) devices, aerial (remote sensing) equipment, software logs, cameras, microphones, radio-frequency identification (RFID) readers, and wireless sensor networks, the size and quantity of available data sets have increased dramatically [1],[2]. Since the 1980s, the global technical capacity per person to store information has approximately doubled every 40 months; as of 2012 [3]. According to a forecast by International Data Corporation (IDC), the worldwide data amount is projected to reach 163 zettabytes by 2025 [4]. Thus, the accumulation of data from many sources leads to high velocity, high volume, and variety of data, which in turn gives rise to the phrase big data has gained popularity recently. The "3V" stands for three major characteristics that best characterize big data: Volume (the total amount of data produced), variety (data spanning numerous categories), and velocity (the speed at which data is produced) [5],[6],[7],[8],[9]. There have been two more "Vs" added: Veracity (the caliber of recorded data) and variability (inconsistency in data) [10].

Numerous scientific fields, including medicine [11] and customized treatment based on genetic data [12], social media [13] and the agriculture areas are using big data applications. One of most and prominent field of big data is in Healthcare. The generation of medical images is growing exponentially as a result of the proliferation of digital devices and the development of camera technology. A digitized image is used by modern hospitals these days to forecast the severity of a patient disorder. Image classification has grown significantly more difficult with the abundance of medical images due to the quick development of digital imaging. In order to allocate these medical images to the most relevant class based on similarity, classification methods must be used. A medical image classification domain contains images of various body organs, including CT scans, X-rays (electromagnetic waves), and positron emission tomography (PET) scans, Magnetic resonance imaging (MRI), and many more

which are a type of imaging test that shows how your body's organs and tissues are functioning. Image classification is now playing a key part with the big data in the medical images because of the development of digital images. Handling with Big data is also a challenging task. In this paper we utilized Lung CT images to diagnose lung disease without disclosing the sensitive information of the patients.

In a variety of machine learning problems [14], deep learning (DL) algorithms have produced exceptional results in recent years. CNN have been shown to be particularly effective at image classification tasks. They have been successfully used in a variety of field's, including the prediction of galaxy morphology [15], the creation of image-guided autonomous vehicles [16], face detection [17],[18], large-scale video classification [19], and many other applications [20],[21],[22]. In the area of pattern identification, CNNs have excelled in particular. In our work, we modify CNN model to classify diseases such as Covid-19, Lung cancer, pulmonary Tuberculosis and Pneumonia.

There may be numerous features in the images of a big data dataset which could have an impact on or worsen our classification model's performance if we include all features. Features can also be related to one another; these features are redundant and inconsequential, which could negatively impact computation time. Feature selecion approaches are presented as a solution to this noise issue, with the potential to eliminate irrelevant characteristics without compromising other pertinent information [23]. The ability to avoid the curse of dimensionality, shorten the training model's runtime, improve data compatibility with the learning model, and enable smoother model interpretation is among the main duties of feature selection [24].

The feature selection procedure can be done by user input interaction with a databank to categorize user disorders; it is most prominent area where sensitive information can be shared or leaked. We may be providing opponents with sensitive information since we are dealing or working with medical images, which are extremely sensitive for each individual. As an illustration, when a user engages with a model by requesting matching features from a databank, the model may learn unique insider information about the person and vice versa. As a result, security and privacy are becoming increasingly important aspects of big data. In this paper, we developed a privacy-preserving system that recognizes similar traits without revealing user's personal information. We accomplish these goals by combining the MLCNN model with privacy preserved cosine similarity.

The paper is divided into the following sections: The literature review is briefly explained in Section 2. Section 3 explains the problem statement. The proposed methodology is presented in Section 4. The experimental findings and results analysis of the proposed investigation are shown in Section 5. Discussion section is presented in Section 6. The conclusion and the scope for the future is presented in Section 7.

2 Literature review

Guo C, et al. [25], the suggested method's security was examined to make sure that no private data from the encrypted images was disclosed. They assess and illustrate the usefulness of the privacy-preserving approach for image searching on four real-world datasets (i.e., chest X-ray images, retinal OCT images, blood cell images, and the Caltech101 image set) as well as CNN-based classification and original image searching. This protocol makes it possible to search for images that are sent to the cloud quickly and accurately without sacrificing the privacy of encrypted data. According to experimental results, PPIS outperforms prior systems in terms of searching time (more than six times faster) and achieves an accuracy rate of over 86% on real-world datasets with the same CNN structure in the plaintext domain.

Qi et al. [26] suggested a ConvMixer model with an adaptive permutation matrix and block-wise encrypted images as a means of classifying images while preserving data privacy in cloud environments. Traditional block-wise scrambled encryption methods usually involve the use of both a classifier and an adaptive network to reduce the impact of image encryption. However, the authors point out that using large-size image with conventional methods that use an adaptation network is difficult because of the significant rise in processing costs. In order to verify that the suggested approach uses fewer computing resources, they also assess the computation cost of cutting-edge privacy-preserving DNNs. The authors conducted an experiment to assess the robustness against different cipher text-only assaults and the classification performance of the suggested method on ImageNet and CIFAR-10 in comparison to other methods. The suggested approach was shown to perform better than traditional approaches in an experiment with regard to classification computation cost, accuracy, and resilience to attack techniques.

Jia et al. [27] presented a novel method for identifying image characteristics that integrates multilevel homomorphic encryption and image data partitioning. This new partitioning technique reduces computational complexity, minimizes processing load, and improves classification accuracy. To improve data security and privacy, the authors proposed a new encryption method for partitioned images that is entirely homomorphic. To address the intrinsic complexity of encryption, they devised a compound encryption technique that harnesses the full potential of homomorphic computation, with the stated goal of reducing computational and storage overheads. The technology offered significant advantages over traditional methods, including increased computational efficiency, lower storage and transmission costs, and

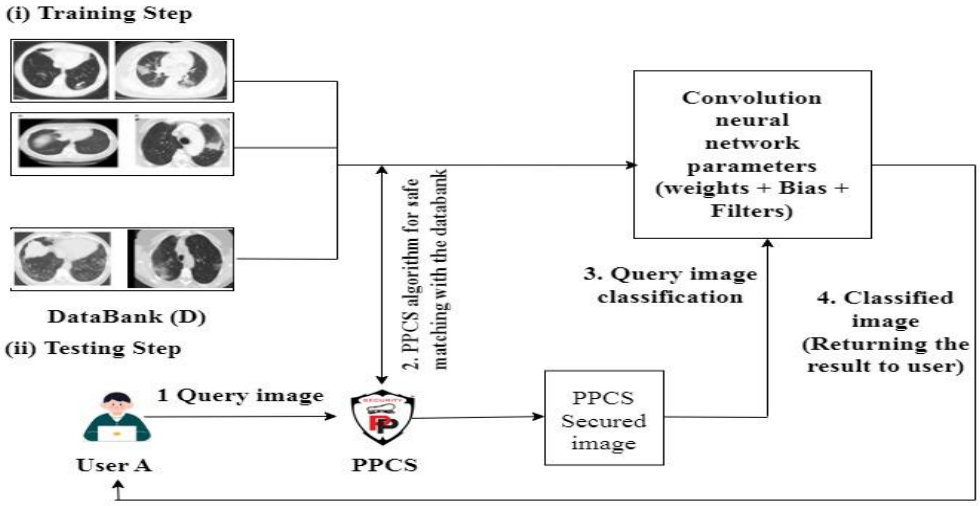

Figure1: Conceptual scheme of proposed work

enhanced security and privacy. This paper's methodology effectively addresses the complex issues of image feature categorization in cloud computing and big data environments.

To determine the most salient features defining a distributed privacy-sensitive dataset, Alishahi et al. [28] developed a unique framework called LDP-FS that combines Local Differential Privacy (LDP) with Feature Selection (FS).The authors presume the features are categorical and independent, and evaluate LDP-FS's performance utilizing two distance measurements: Kendall Tau distance and RMSE, which demonstrate LDP-FS's effectiveness in predicting feature importance scores and ordering features. The experimental findings show how effective and helpful LDP-FS is at detecting irrelevant features in protected data.

Sadoon et al. [29] the author presents the application of cutting-edge techniques, including artificial neural networks, transfer learning, and stacked ensemble models, to create a model with previously unheard-of accuracy, precision, recall, and F1-score. The most dependable classification tool and the best performance are obtained when DenseNet, Xception, and Inception are combined. Additionally, they employ transfer learning to optimize generalization and rapidly train the model, which enables it to detect a variety of pulmonary diseases, including COVID-19. The given research suggested the effective fusion of state-of-the-art deep learning techniques and image processing algorithms with the particularities of the medical imaging sector.

Nemer Z N. et al. [30] given the numerous advantages that sea coral and its classes offer in many facets of our lives, they have developed a system in this study to categorize the sea coral images. Studying four CNN architecture models—AlexNet, SqueezeNet, GoogleLeNet/Inception-v1, and Google Inception-v3—is crucial to this work because it allows researchers to assess each architecture's accuracy and efficiency and identify which one performs best on coral image data. The specifics are provided in the research paragraphs. AlexNet, SqueezeNet, and GoogLeNet demonstrated accuracy of 83.33%, 80.85%, and 93.17%, respectively, according to the results.

Depend on the model architecture and classification difficulty, there are notable differences in accuracy when comparing deep learning models using with secure data in medical image classification. Table 1 illustrates that secure image classification presents difficulties in sustaining high accuracy, when dealing with big data computational resources.

Through the integration of a PPCS and MLCNN, our suggested architecture successfully tackles the pressing issue of data breaches in medical AI classification pipelines. The MLCNN component of the framework uses deeper multi-layer training to enable the network to learn complex hierarchical features that are essential for accurate classification of lung conditions. The architecture is designed to ensure both high diagnostic accuracy and data privacy, which are crucial when handling sensitive medical imaging data like CT scans. PPCS, on the other hand, is essential to preserving data privacy during the search and categorization process. Direct image search and similarity comparison on these encrypted representations are made possible by the PPCS protocol. This is achieved by using a privacy-preserving regularization function that guarantees no identifiable information is leaked in the intermediate or final findings, even during image retrieval or classification. The combination of PPCS and MLCNN allows for a reliable, privacy-conscious medical image analysis system that combines CNNs' deep feature learning capabilities with the advantages of secure computation. The end product is a pipeline that rigorously complies with data privacy regulations while supporting high-accuracy forecasts.

Table 1: Comparisons for related works

Study	Method	Dataset	Privacy	Performance
[25]	Privacy-preserving, image-searching protocol + CNN	Chest X-Ray Images + Blood Cell Images + Caltech101 image +Retinal OCT Image	Secure Multiplication (SMP), Secure Squared Euclidean Distance (SSED), Secure Convolution (SCV), Secure Max Pooling (SMPL)	Precision: Chest X-Ray-89.5%, Retinal OCT - 89.6%, Blood Cell- 86.3%, Accuracy-86%
[26]	Privacy-preserving + ConvMixer	CIFAR-10 + ImageNet	Privacy-preserving wise encryption method	Accuracy CIFAR-10-92.65%, ImageNet - 76.94%
[27]	Homomorphic encryption + CNN	NEU-CLS data set	Multilevel homomorphic encryption	Accuracy - 97.1%
[28]	Differential Privacy + Machine Learning	UCI Repository	Local Differential Privacy Feature Selection	Census- Optimal Local Hashing - 94.1%, Optimized Unary Encoding- 94.1%, Thresholding with Histogram Encoding-94.1%, Mushroom OLH-90.2%, OUE-90.2%, THE-90.2% Obesity OLH-91.2%, OUE-91.2%, THE-91.2%, KDD99 OLH-99.8%, OUE-99.8%,THE -99.8%
[29]	Combination of DenseNet, Xception and Inception	COVIDx, CXR-4 Datasets	No	Precision- 98%, Recall- 98%, F1-score- 98%, Accuracy- 98%
[30]	AlexNet, SqueezeNet,GoogLeNet/ Inception-v1, google Inception-v3	10 classes of sea coral images	No	Accuracy AlexNet -83.34%, SqueezeNet - 80.86%, GoogLeNet - 90.6%, Inception-v3 - 93.18%

3 Problem statement

We investigate a viable solution to the problem outlined in this study. To maintain anonymity, two bodies, A (user) and B (model), want to work together to execute a common image similarity detection algorithm using their private inputs. A represents the user who possesses a private image I. B denotes the model that classifies diseases related to the lungs. D refers to the databank that provides a collection of images. Let D = (I1, I2, I3, I4…….. In) refers to represent the collection of n images that D has. It is possible that additional information for both sides may be sacrificed if a user wishes to transmit a private image I as input to the pre-trained model in order to determine patient disease. To diagnose the disease, we must first determine the cosine similarity between the feature vectors in the database together with the query image I in a secure way before feeding the data straight into the model. Our goal is to find the image in D that most closely resembles Ụ while protecting the patient's and model's privacy.

Our approach, which uses PPCS, is more adaptable to such circumstances. PPCS can assist in safely extracting comparable features from the database. The PPCS method is the first thing the model will utilize if the user wants to enter a query image (CT image) to identify lung-related conditions. By employing cosine similarity with every databank image, PPCS safely locates features and returns a response with a privacy-preserved image. After the classification of the privacy-preserved image by our MLCNN model, the user receives the results (Figure 1).

4 Proposed scheme

Preliminaries

4.1 Examination of the dataset for chest CT

In this study, the chest CT scans have been used to detect Covid-19 inside our dataset. Information was taken from the Moscow Health Care Department's Research and Practical Clinical Center for Diagnostics and Telemedicine Technologies, which provides the labeled and open-source MosMed database. It comprises 1110 unique CT chest images. Comparatively, 684 scans

demonstrate stage#1 COVID-19-related pathology, 125 shows stage#2, 45 shows stage#3, and 2 shows stage#4 disease patterns, which identify different stages of disease progression. The Dataset also includes some more data categorized by nation. The Ning W [31] dataset, which came from two respectable hospitals in China (Liyun Hospital and Union Hospital), was also used. The images in this dataset were categorized into three groups: non-informative images (5705), Covid –ve cases (9979), and Covid +ve cases (4001). Thus, a total of 19,685 CT scans with labels are gathered. The Russia [32] dataset and Brazil [33] dataset is also included in our dataset. The Brazil dataset, which has 2482 CT images from 120 individuals. The data was divided into two groups: 1252 CT images for covid +ve cases and 1230 images for covid -ve cases. A publicly available dataset of Iran has been used that contains 8,439 scans images, which are categorized by 7,495 scans for positive cases and 944 scans for negative.

In our experiment, we used the LIDC-IDRI [34] dataset, which is open to the public. Prior studies on lung nodule identification solely took into account the nodule's diameter, which had to be at least 3 mm in order to ensure consistency for the assessment and subsequent comparison with the suggested structure. The size of the nodule and its edge, which is equally crucial for diagnosing lung cancer, are two significant metrics that we have examined in our work. In essence, a spherical nodule has a lower risk of cancer than a circular one (which has sharp edges).

Some helpful datasets, like the Radiological Society of North America (RSNA), and Radiopaedia, have medical and public datasets that are thought to be the most common. These collections of common pneumonia CT images, which total roughly 4846 images [35], [36], can be used to train our proposed deep MLCNN to differentiate COVID-19 from pneumonia.

There are pulmonary tuberculosis samples available for study and advancement. These include the multi-category segmentation dataset DeepPulmoTB, as well as datasets from the National Institutes of Health (NIH), Hugging Face etc [37]. These datasets provided useful tools to examine and comprehend pulmonary tuberculosis using CT images. This study's final dataset, which includes 2500 CT images, is of normal images.

4.2 Data storing phase

Due to the rapid increase in lung diseases, including, COVID-19, Lung cancer, pulmonary Tuberculosis and Pneumonia, it is essential to analyze diseases using a multi-classification approach. In order to accomplish this, we are working with extensive datasets from multiple sources, which are challenging due to their varying conventional shapes, sizes, and formats.It is critical to handle this massive amount of data in accordance to process and storing. Apache Spark, one of the most popular frameworks, efficiently stores large amounts of data and distributes the processing of the data, either inside the same system or in combination with other distributed computing technologies.

In our approach, we build end-to-end deep learning pipelines that operate on the Spark platform are built using the Python packages PySpark, TensorFlow, and Elephas. We utilized PySpark to access the Python API in Spark [38], which expands Apache Spark's capabilities and allows for Python operations.

The Apache Spark architecture is seen in Figure 2 and includes a driver programme that aids in running the system's primary purpose and creating Spark Context objects. To operate the processes on a cluster, Spark Context connects with many kinds of cluster managers.

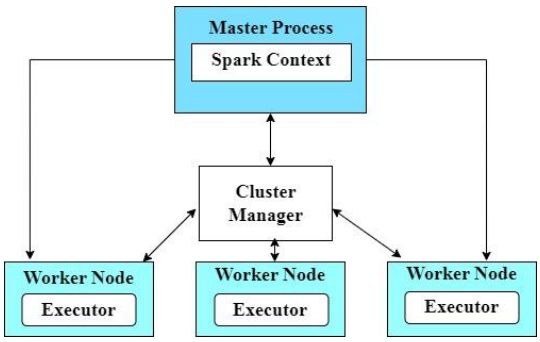

Figure 2: Overview of the apache spark cluster

It obtains the executor from the cluster nodes and then passes our system jobs to the executor so that it can execute the job. The cluster manager is responsible for allocating the resource across the systems. Cluster managers are available in various types, including Apache Mesos, Hadoop YARN, and standalone schedulers. The application running on the cluster is supported by the worker or slave nodes.

To complete our task, we must first decode the images into a Spark dataframe. To do this, SparkSession is set up to access the fundamental Spark features for DataFrames with dispersed master clusters. We loaded all images from folders into the DataFrame using the Apache Spark SQL data source API, utilizing a single column named "image". Image augmentation has been used to carry out operations like rotation, skewing, and reversal. After the image size of 224 x 224 x 3 has been achieved, each block of the image can be distributed to RDD in order to create a faster and more efficient map and minimize operations.

4.3 Training the model

4.3.1 Feature extraction

The feature extration procedure reduces dimensionality during the predictive model construction process by removing superfluous and irrelevant features from the input image. There are algorithms in deep learning that

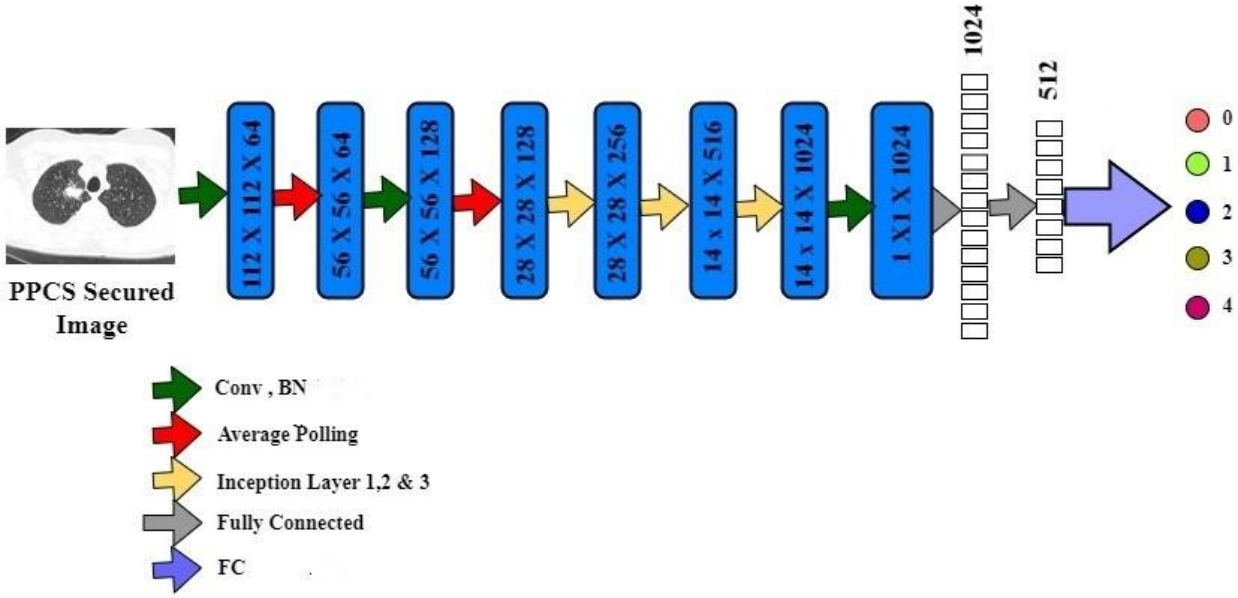

Figure 3: MLCNN Architecture to classify Lung images

choose features automatically as part of the model-learning process. Convolutional neural networks, or CNNs, have been widely used in medical image processing and have produced significant benefits for public health in the field of medicine [39].

There are three primary layers in the proposed MLCNN. Extracting hierarchical characteristics from the encrypted input image is the goal of these layers.

The first layer is convolutional layer receives data from the input layer and processes it. The convolutional layer, the central layer of the neural network, has the ability to improve feature information and eliminate irrelevant information. The output of neurons connected to the input is calculated by each convolutional layer using a dot product of the weights of the neurons and a small portion of the input to which it is connected. Equation (1) provides the output of the neurons at the first convolutional layer, where x is an input feature map and w is the weights .

$$\gamma^k = f\left(\sum_{k=0}^{k} x^k .\ w^k + b^k\right) \tag{1}$$

Where dot denotes the 2D convolution operation between input feature map and weight w. γ^k is the convolutional layer's output feature map for the k^{th} input, with b serving as the bias term. With 64 kernels, the convolutional layer-1 generates output in a volume of 56 x 56 x 64.

While CNNs are built for encryption image contexts, polynomial activation functions are crucial because they allow for secure computation by substituting operations that can be carried out on encrypted data (such as additions and multiplications) for conventional non-linearities. This ensures interoperability with privacy-preserving frameworks while maintaining the model's capacity to learn intricate patterns. By using simply addition and scalar multiplication, it offers effective spatial downsampling that is compatible with homomorphic encryption. It also produces smoother and more stable feature aggregation without the need for non-linear operations like max pooling.

The Conv and Poly activation functions are separated by batch normalization (BN), which expedites training and reduces network initialization sensitivity [40]. The internal covariate shift is intended to be eliminated by BN. This is accomplished by normalizing the batch-wise mean (μ) and standard deviation (σ).

The mean and variance (σ^2) are computed using the following formulas for batch normalization computation.

$$Mean(\mu) = \frac{1}{n}\sum_i^n x_i \tag{2}$$

$$Variance\ (\sigma^2) = \frac{1}{n}\ x \sum_i^n (x_i\ - \mu_i) \tag{3}$$

Here n is the mini-batch size of the x_i input feature element, while μ and σ are the mini-batch mean and standard deviation, respectively. In our case, n is set of 64

$$\gamma_i = \frac{(x_i - \mu_i)}{\sqrt{\sigma 2 + \varepsilon}}\gamma + \beta \tag{4}$$

Where the initial values of each output's learnable parameters are γ and β.

Lastly, the pooling layer divides the neurons of the previous layer into a set of non-overlapping rectangles and utilizes a down sampling technique to extract the value of one neuron from each sub-area in current layer. In average pooling the output is selected as the average value within each sub-region. With stride 2, a 2 x2 avg-pooling is used for down-sample the feature map produced by the previous sub-layer in our work. Each successive convolutional layer's feature map is immediately pooled

by computing its maximum polynomial activation output, as indicated in Equation (5).

$$\gamma_{PooL} = AVG_{PooL}\left(Poly\left(BL\left(Conv(x, \text{ẇ})\right)\right)\right) \quad (5)$$

Table 2 illustrates that the input provided to the proposed MLCNN model is of size 224 × 224 × 1. In the first stage, the model employs a convolutional layer (Conv_1) with 64 filters of size 7×7 to extract initial features. In the subsequent stage, a second convolutional layer (Conv_2) is applied, using 128 filters of size 3×3 to capture more detailed and higher-level features essential for accurate disease identification. Since we are dealing with homomorphically encrypted images, it is crucial to make sure that every CNN operation is compatible with the restrictions of homomorphic encryption techniques. The ReLU activation function and max pooling are examples of standard non-linear processes that depend on conditional logic and comparisons, which homomorphic encryption does not natively enable. Polynomial activation functions, which can be easily calculated using addition and multiplication, were used in place of ReLU in order to overcome this. Likewise, we replaced max pooling with average pooling since it works with addition and scalar multiplication, which are fully supported by homomorphic encryption. After each Convolution layers (Conv_1 and Conv_2), polynomial functions and average pooling layers (AP1, AP2, AP3 and AP4) have been applied. With these modifications, MLCNN inference is safe and private without disclosing computational feasibility. After that Inception layers (I1, I2, and I3) are employed which is the combination of Convolution layers followed by polynomial function and average pooling. In order to reduce dimensions utilizing stacked 1x1 convolutions and enable more efficient computation in the deeper networks, convolutional neural networks use inception modules. These modules are designed to address a number of issues such as computational cost and overfitting. The final two fully connected layers (FC1 and FC2) are added to classify the diseases . To prevent overfitting, a dropout layer is added after the last pooling layer for regularization. Figure 3 shows the architecture of the proposed model.

4.3.2 Classification

The feature map obtained from the Inception layer is flattened into a one-dimensional array, and a dense fully connected layer with the poly activation function is then added in order to categorize the diseases into five groups (COVID-19, Lung Cancer, pulmonary Tuberculosis, Pneumonia, or Normal). To anticipate the result, the dense layer uses the features that were recovered from the processed images; the poly activation is applied as the final layer.

Algorithm 1: Fast identification and classify large size images

Input: Lung CT image (including all diseases images) Training_Set δ1 and Testing_Set δ2 Learning rate – μ, iteration step – ξ;

Step1- import required libaries
import pyspark // Setup a pyspark session
import tensorflow as tf
import elephas // DL receives tensorflow. keras to spark from the deep learning pipeline.
from tensorflow.keras.models import Sequential as Seq
from tensorflow.keras.layers import Conv2d,Flatten, Dense_d,AvgPooling2D, Dropout_Lr
from tensorflow.keras layers import Dense, Dropout, Conv2d, AvgPool2d, Fattern, Activation, Batch Normalization.

Step2- Create a Spark dataframe with all of the images loaded, and then divides it into training and testing sets. // the capacity to study data in multiple analytical ways is provided by Spark Data Frame.

Step3- // to categorize lung_images

L#3.1: (Conv2d) layer_Conv1= Conv2d (filters_f= 64,(filter_size_L1 = 7,7);input_shape=(224,224,3) stride_s=2; padding_p=same; activation_act='poly') (ɣ)

L#3.2: (Conv2d) layer_Conv2= Conv2d (filters_f= 128,(filter_size_L2 = 3,3); stride_s=1; padding_p=same; Activation_act='poly') Avg_Pooling2d(2,2)

L#3.3,3.4,3.5: def incp_mod(a, F_1x1, F_3x3,F_avgpool, name= None):
Output = concatenate ([Conv2D_1x1, Conv2D_3x3,AvgPool_1, Droupout]
Dense layer // auxiliary _outputs

Step4– Fit and analyze the model

Table 2: A tabular representation of the proposed model that includes the kernals, output shape, and learnable parameters used

Layer (type)	**Kernel size**	**Output shape**	**Learnable Parameters**
Conv_1	7x7, s=2 f#64	112, 112 , 64	9.4k
AP1(AVG P_1)	2 x2/2	56, 56, 64	0
Conv_2	3 x 3,s=1f#128	56,56, 128	75 k
AP2(AVG P_2)	2 x2/2	28,28, 128	0
InceptionM(I_1)	1 x1conv, 3x3 conv, AVG_Pool	28,28, 256	300k
AP3(AVG P_3)	2 x2 /2	14, 14, 256	0
InceptionM(I_2)	1 x1conv, 3x3 conv, AVG_Pool	14,14, 512	76.6k
InceptionM (I_3)	1 x1conv, 3x3conv, AVG_Pool	14,14, 1024	160k
AP4(AVG P_4)	2 x2/2	7 ,7, 1024	0
FC1	Linear	1,1, 1024	5M
FC2	Linear	(None, 5)	5k
Total parameters: 51,763,845			
Trainable parameters: 51,763,743			
Non trainable paramerters: 102			

4.4 Testing the model

4.4.1 Querying image

The suggested model's basic architecture is depicted in Figure 1. The user provides a CT scan as input to diagnose illnesses during the testing phase. The security of the user, model, and databank must be considered. Using the PPCS method, we first safely extract lung features from the databank to confirm whether the image belongs to the lungs and to detect harmful or noisy data. A compression level of M=0.6N is then applied to the image, where M represents the compressed measurements and N represents the original dimension. In order to protect sensitive user and databank information, PPCS makes sure that an encrypted and protected image is shared with the MLCNN model.

4.4.2 The functionality of PPCS

By comparing the input image to every other image in the database, the PPCS method determines similarities without jeopardizing model security or user personal information. Based on certain fully homomorphic encryption [41], privacy-preserving aggregate is a widely used method of gathering data for event statistics. If a public key encryption method E(*) is homomorphic, then many sources can encrypt their own data (m1, m2, m3…….. mn) using the same public key to create ciphertexts (ct1 = E(m1), ct2 = E(m2), …, ctn = E(mn). For instance, these ciphertexts can be accumulated as follows: $C = \prod_{i=1}^{n} ct_n = \sum_{i=1}^{n} m_i$ using the sum aggregation. It is possible to recover the accumulated result $\sum_{i=1}^{n} m_i$ from ciphertexts using the matching private key. To ascertain commonalities, we compute the dot (*) product of two images represented as vectors and divide it by the magnitudes of each feature vector map. All of the image properties in the database are compared to the input feature's cosine values. The cosine similarity range is between -1 and 1. Two vectors with the same orientation will have a high cosine similarity when their angle is 0.

PPCS Algorithm 2

The steps involved in the cosine similarity computation process are as follows:

P_A = Image of Patient A

And feature vector $a = (a_1, a_2, \ldots\ldots\ldots a_m)$

D_B = Database Image B

And feature vector $b = (b_1, b_2, \ldots\ldots\ldots b_m)$

Step1: Generation of keys (α, β):

i) Determine that by choosing two different prime numbers, α and β.

ii) $\eta = \alpha*\beta$ and Security parameter

$\lambda = \text{lcm}(\alpha\text{-}1, \beta\text{-}1)$, where the least common multiple is shown by the lcm operation. Assume that the private key is λ.

iii) Select an integer at random $g \varepsilon Z^2$.

iv) Make sure the following modular multiplicative inverse exists in order to verify that η divides g's order.

$\mu = L(g^{\lambda} \bmod (\eta^2))^{-1} \bmod \eta$

The function can then be defined = $\frac{\mu-1}{\eta}\lambda$;

The public key pk will be (g, η); transmit it to UA for additional calculation.

Step2: Encryption (a, pk) : Computation on UA

i) Choose an integer at random $r \in \dot{Z}*\eta^2$ (A number between 1 and η^2) for everya_i, i =1,2,...,m

ii) Calculate $C_i = g^{a_i} r^{\eta} \bmod \eta^2$

where $a_i = (a_1, a_2, \ldots\ldots\ldots a_m)$

iii) Transmit (g, η, C_i) toD_B

Examine $A = \sum_{i=1}^{m} a_i^2$

Step3:D_B Calculation (calculated for each input database image)

For each bi , i= 1,2,.. m $D_i = g^{a_i} r^{\eta} \bmod \eta^2$

$B = \sum_{i=1}^{m} b_i^2$ and $D = \sum_{i=1}^{m} D_i$

Transmit (B, D) to UA

Step4: Calculation by UA:

Find out $E = r^{-\eta}.D \bmod \eta$

$\vec{a}.b = \sum_{i=1}^{m} a_i b_i$

$$= \frac{E - (E \bmod r^2)}{r^2}$$

$$\cos(\vec{a}.\vec{b}) = \cos \frac{\vec{a} * \vec{b}}{\sqrt{A}\sqrt{B}}$$

Now, without revealing the model or user data, the subset is produced. Consequently, the private information of the model and its users is safe, and there is no chance of a security breach from either side.

We can efficiently compute the cosine similarity cos (a,b), given $a = (a_1, a_2, \ldots\ldots\ldots a_m)$ and $b = (b_1, b_2, \ldots\ldots\ldots b_m)$. However, Inter-big data processing would make each other's privacy visible through the direct cosine similarity evaluation. We used FHE, CSSK scheme, to execute the privacy-preserving cosine similarity computation by first computing $\vec{a}.b$ and then $\cos(\vec{a}.\vec{b})$ using the values of $\vec{a}.\vec{b} = \sum_{i=1}^{m} a_i b_i$. Since each a_i i = 1, 2,…, m is randomly masked with $C_i = g^{a_i} r^{\eta} \bmod \eta^2$, Algorithm guarantees that each $a_i$is privacy-preserving for the purposes of PPCS. It should be noted that the purpose of adding $a_{n+1} = a_{n+2} = b_{n+1} = b_{n+2} = 0$ is to guarantee that D contain a arbitrary integer, ŕ. The vector $b = (b_1, b_2, \ldots\ldots\ldots b_m)$can be prevented from being guessed by vector a.

Table 3: Findings of lung CT image classification in various rounds

		MLCNN					MLCNN with PPCS				
		CP	**LC**	**PT**	**PN**	**H**	**CP**	**LC**	**PT**	**PN**	**H**
20 rounds	CP	**2847**	809	547	691	96	**4747**	689	215	896	67
	LC	353	**3785**	479	275	450	367	**3993**	354	537	518
	PT	722	200	**3265**	198	283	868	419	**4215**	749	317
	PN	443	176	325	**3673**	205	653	299	134	**2478**	191
	H	506	516	274	163	**3966**	765	475	82	340	**3910**
50 rounds	CP	**4926**	410	769	78	164	**5726**	595	67	68	279
	LC	902	**5888**	379	25	93	925	**5925**	83	98	92
	PT	707	1325	**7515**	46	177	1360	2136	**10335**	111	240
	PN	821	1008	176	**8834**	145	1356	1056	121	**9723**	45
	H	675	259	413	42	**9566**	843	288	223	123	**9389**
100 rounds	CP	**15098**	565	136	67	337	**14565**	1065	153	131	370
	LC	1387	**17271**	267	133	154	1986	**17226**	241	43	162
	PT	1455	478	**21665**	243	870	1723	298	**22465**	126	549
	PN	1381	616	312	**19800**	132	947	486	183	**19775**	231
	H	1589	970	139	121	**21331**	1889	925	142	180	**21186**

4.4.3 Classification for querying image

As illustrated in Figure 3, we provide the private, encrypted analysis of the parameters to calculate the querying image's feature vector in order to build a forward propagation structure. Thus, the tensor variable v indicates the feature mappings of each layer.

5 Results and discussion

5.1 Experimental parameters

The Tensorflow 2.10.1 framework and Python 3 were used to create the models. Apache Spark 2.4 with a P100 GPU processor, 2 TB of storage, and 32 GB of RAM was used to run these. Using an API Keras Augmentor, the images of the input classes were enhanced to increase the amount of images in each class in order to achieve the statistical findings. To carry out pre-processing tasks like augmentation, scaling, and normalization, all original and augmented images were sent to Keras Image Data Generator class [42].

5.2 Performance metrics

For all training images, we determine effectiveness and accuracy of the model with the help of the confusion matrix (COM). It has 4 variables: True positive ($True_P$), False Positive ($False_P$), False Negative ($False_N$), and True Negative ($True_N$). To measure or evaluate the effectiveness of a model, the rows in the matrix represent the original class values, while the columns represent the estimated class values. Furthermore, according to Equation (6), Accuracy (AC) is calculated using a confusion matrix that takes into account the proportion of correctly evaluated specimens to all specimens. Equation (7) defines precision (PC) as the positive predicted value, and recall or sensitivity, as used to classify as positive corrected specimens that yielded a positive result shown in Equation (8). While specificity (SF), as shown in

Equation (9), refers to the true negative rate. In addition, the Matthew's Correlation Coefficient (MCC) is also mentioned in Equation (10), and F1-score is specified in Equation (11).

$$Accuracy\ (AC) = \frac{True_P + True_N}{True_P + True_N + False_P + False_N} \quad (6)$$

$$Precision(PC) = \frac{True_P}{True_P + False_P} \quad (7)$$

$$Recall\ (TPR\ or\ Sensitivity) = \frac{True_P}{True_P + True_N} \quad (8)$$

$$Specificity(SP) = \frac{True_N}{True_N + False_P} \quad (9)$$

F1-score illustrates how Recall and Precision are used to generate the F1 score. Compared to other scores, such as MCC, the F1 score provides a more balanced perspective; nonetheless, it may produce a biased result by ignoring the number of True Negatives. As indicated by Equation (9), the Matthew's correlation coefficient [43] takes into account each and every cell in the confusion matrix.

$$MCC = \frac{(\boldsymbol{True_P} * \boldsymbol{True_N}) - (\boldsymbol{False_P} * \boldsymbol{False_N})}{\sqrt{(\boldsymbol{True_P} + \boldsymbol{False_P})(\boldsymbol{True_P} + \boldsymbol{False_N})(\boldsymbol{True_N} + \boldsymbol{False_P})\ \boldsymbol{X}\ (\boldsymbol{True_N} + \boldsymbol{False_N})}} \quad (10)$$

$$F1 - score = \frac{2 * PC * TRP}{PC + TRP} \quad (11)$$

MCC and F1-score have been performed on the experiments result which evaluates the system model's performance. Initially, the suggested deep learning model was trained to recognize CT images based on five categories: COVID-19, lung cancer, pulmonary Tuberculosis, Pneumonia, and normal. The CT images were then tested using the deep learning model. The suggested deep learning model's potential is assessed using a technique for 5-fold cross-validation for the classification problem.

For every fold, multi-class classification and average prototype classification are assessed. The suggested

framework classified COVID-19, lung cancer, pulmonary Tuberculosis, Pneumonia, and normal categories which provide excellent level of classification accuracy. The input CT images with dimensions 224 x 224 x 3 were split into 80% training and 20% testing data.To reduce overfitting, the MLCNN implementation includes dropout layers with a rate of 0.5 following each dense layer. Early stopping was utilized to train the model based on validation loss for up to 300 epochs. The Adam [44] optimizer was employed to maintain a parameter learning rate of 0.05 utilizing the AdaGrad. It improves our model's performance.

Figure 4 represents the average accuracy and loss over the number of epochs during the training and validation stages for the suggested models. We can see how model performance increases throughout training for various communication rounds configurations (20, 50, and 100) in the accuracy graph, the X-axis shows the total effective epochs, which are determined by multiplying the number of rounds by the number of local epochs per round. The validation accuracy percentage is displayed on the Y-axis. As learning stabilizes, the accuracy increases in a smooth, logistic-like fashion before plateauing close to 98.89%, suggesting that the model is doing well. The 20-rounds setup may run the risk of overfitting or instability, but it tends to converge more quickly due to its greater local epochs each round. The rise in the 100-rounds design is more gradual, indicating smaller local updates but more frequent communication. The Loss graph tracks the model's loss (such as cross-entropy) as training goes on, the X-axis shows the total number of effective epochs, and the Y-axis shows the validation loss value, which normally ranges from 1.0 to 0.04. As the model gains insight

Table 4: Confusion matrix for the proposed model

	Normal	Lung Cancer	Covid-19	Pneu-monia	Tuber-culois
Normal	0.9712	0.0561	0.0083	0.0005	0.0011
Lung Cancer	0.0267	0.9712	0.0925	0.0003	0.0001
Covid-19	0.0111	0.0036	0.9790	0.0824	0.0130
Pneu-monia	0.0110	0.0271	0.0212	0.9812	0.1210
Tuber-culosis	0.0121	0.0129	0.0218	0.0250	0.9822

from the data, each curve gradually drops from its starting greater loss value (about 1.0), which indicates bad initial predictions. Because to data noise and stochastic optimization, the loss exhibits an exponential decline pattern with slight oscillations. A loss value near 0.04, which denotes a well-trained model, is the goal of all setups. While the smooth drop in many rounds represents slower but steady development, the steeper curves in fewer rounds suggest faster local convergence.

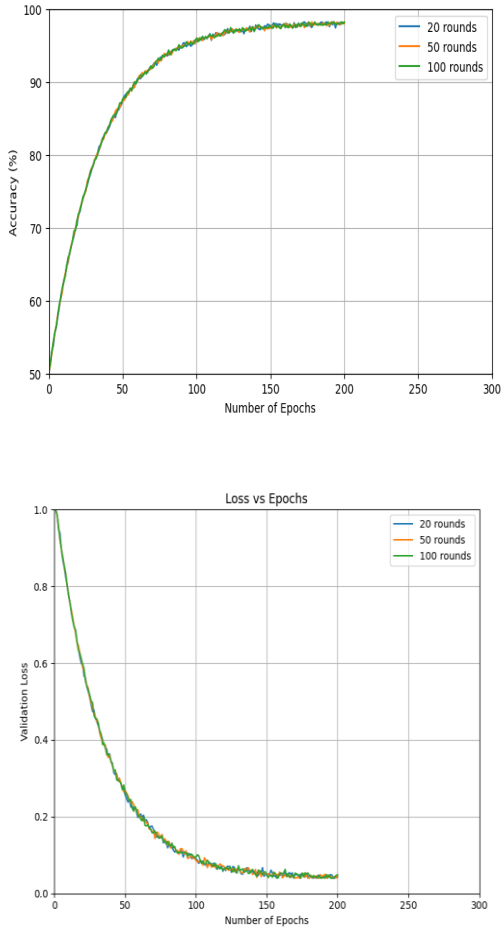

Figure 4: Average accuracy and loss, over the number of epochs in the training and validation stages

The accuracy (AC), loss, recall (Sensitivity), positive predictive value (PPV), also referred to as precision (PC), specificity (SF), negative predictive value (NPV), F1-score, Matthew's correlation coefficient (MCC), and area under the curve (AUC) were among the metrics used to assess the effectiveness of the lung disease classification models.

Before sending the query image to the model, this method offers a better technique to remove irrelevant (private) features. Consequently, categorization performance is one metric that can be used to assess our approach. Here, classification and feature similarity searching are done using the PPCS technique, with MLCNN and without PPCS serves as the baseline for classification. The categorization results with MLCNN with and without PPCS for the medical datasets are shown in Table 3, Covid, lung cancer, pulmonary Tuberculosis, Pneumonia, and normal patients are denoted by the terms CP, LC, PT, PN and H respectively

Table 5:Measures of evaluation for various models

Model & Authors	**Dataset**	**Accuracy**	**Recall**	**Precision**	**F1-Score**
Salih Ahmed et al. [45]	Kaggle CXR	98.72%	Covid - 96.27%, Non findings- 99.3%, Pneumonia- 99.66%, Tuberculosis - 98.10%	Covid - 97.00% Non findings - 98.72%, Pneumonia - 99.89%, Tuberculosis - 98.90%	Covid- 96.63%, Non findings- 99.04%, Pneumonia- 99.77%, Tuberculosis- 98.50%
Jia et al. [27]	NEU-CLS	97.1%	-	-	-
Nemer et al.[30]	sea coral images	AlexNet (AC)- 83.34% , SqueezeNet (AC) - 80.86% , GoogLeNet (AC) - 90.6% Inception-v3 (AC)- 93.18%	-	-	-
Kulkarni et al. [46]	Multiclass Kaggle dataset and the NIH dataset (COVID-19, Pneumonia, TB)	97%	98%	97%	Covid - 97%, Pneumonia - 96%, TB- 0.98%
PPCS+ MLCNN	Covid-19, Lung cancer, pulmonary Tuberculosis, Pneumonia, or Normal	98.89%	98.38%	98.89%	98.54%

in this context. Several classification rounds are carried out using different test sets of the same size following the model training procedure. The Table displays the number of accurate and inaccurate predictions for each class. This facilitates comprehension of the classes that the model is mistaking for another class. The PPCS+MLCNN model outperformed standard MLCNN when it came to lung medical images. The five explained lung disorders can be reliably and automatically identified by our proposed procedure.

In deep learning, some stochastic training effects are required to demonstrate the stability or dependability of the outcomes such as Confidence interval (CI), which indicates that results are trustworthy and that the true accuracy is near our reported mean and Standard deviation (SD). SD indicates that our model performs consistently throughout training runs. We computed this for our model using five-fold validation and 100 rounds. Since the SD is approximately 0.04(SD = 0.1%, which is quite low and indicates strong stability), the values are closely grouped. A 95% confidence interval [98.01% - 98.03%] is attained, indicating a closely defined confidence interval.

As seen in Table 4, we constructed the confusion matrix for the suggested PPCS+MLCNN model. Having the greatest proportion to the standard images (0.9712), lung cancer (0.9712), COVID-19 (0.9790), pneumonia (0.9812), and Tuberculosis (0.9822), the table demonstrates that the PPCS+MLCNN model can successfully classify the five patient statuses (COVID-19, Pneumonia, Lung Cancer, Tuberculosis and Normal). This outcome guarantees that the five statuses are accurately classified.

We also demonstrated disease-wise comparisons between our results and the pre-existing model that identifies certain diseases in Table 6, 7, 8 and 9.

Table 6: Measures for the Covid-19 evaluation

Model and Reference	Disease	Dataset	Accuracy	F1 score	Precision	Recall	Privacy
(VGG19 + Attention CNN) [47]	Covid-19	MosMed database+ curated dataset of COVID-19 lung CT scans	97.52	-	95.71	98.53	Yes
PPCS + MLCNN	Five Lung diseases	Covid-19, Lung cancer, pulmonary Tuberculosis, Pneumonia, and Normal lung Dataset	98.89	98.54	98.89	98.38	Yes

Table 7: Measures for the lung cancer evaluation

Model and Reference	Disease	Dataset	Accuracy	F1 score	Precision	Recall	Privacy
CNN (GoogleN-et + Vgg16) [48]	Lung Cancer	Sathybama Hospital, Chennai CT images	98	98	99	99	No
PPCS + MLCNN	Five Lung diseases	Covid-19, Lung cancer, pulmonary Tuberculosis, Pneumonia, and Normal lung Dataset	98.89	98.54	98.89	98.38	Yes

Table 8: Measures for the pneumonia evaluation

Model and Reference	Disease	Dataset	Accuracy	F1 score	Precision	Recall	Privacy
VGG19 + CNN [49]	Pneumonia	COVID-19, pneumonia, and lung cancer Dataset	98.05	98.24	98.43	99.5	No
PPCS + MLCNN	Five Lung diseases	Covid-19, Lung cancer, pulmonary Tuberculosis, Pneumonia, and Normal lung Dataset	98.89	98.54	98.89	98.38	Yes

Table 9: Measures for the Tuberculosis evaluation

Model and Reference	Disease	Dataset	Accuracy	F1 score	Precision	Recall	Privacy
VGG19 + CNN [50]	Tuberculosis	Pulmonary TB CT image dataset	96.08	-	95	96	No
PPCS + MLCNN	Five Lung diseases	Covid-19, Lung cancer, pulmonary Tuberculosis, Pneumonia, and Normal lung Dataset	98.89	98.54	98.89	98.38	Yes

6 Discussion

An experiment comprising combinations of Networks VGG19, GoogLeNet, Inception V3, AlexNet, and the proposed network were carried out to determine the best performing model. The metrics of performance made by many well-known CNN pre-existing models to diagnose lung disorders in terms of Loss, accuracy, precision, recall, F1-score are displayed in Table 5.

By providing a single point of detection instead of requiring multiple programs to identify each disease independently, the proposed work can be considered the most recent attempt to introduce a single deep learning model to identify various underlying chest ailments. This shortens the decision-making process and eases the burden on the user.

State-of-the-Art comparison: Privacy-preserving image search (PPIS) [25] obtained an average 86% accuracy rate (Chest X-Ray, Retinal OCT, Blood Cell). Our model performs better than this since it continuously maintains high accuracy in increasingly intricate multi-class scenarios. The reason for this growth is that our approach may jointly optimize features from MLCNN integrated inception layer architecture. The author employed a basic CNN model while providing an effective security approach.

Qi et al. [26], images encrypted using the suggested encryption technique were satisfactorily classified with comparatively less processing by the ConvMixer model with an adaptive permutation matrix. However, there are still gaps to obtain accurate classifications, although the authors employed two networks for the datasets: ConvMixer-512/16 obtained 89.14% accuracy and ConvMixer-512/16+ achieved 92.65% accuracy for the CIFAR-10 dataset. However, compared to a model trained on unencrypted images, which was ground breaking work in this field, the strategy did not significantly increase the calculation cost.

Jia H. et al. [27] the study offers a new method for classifying images that protects data privacy by using a modified CNN and encrypted image chunks. They use CNN to carry out the encrypted classification system after first dividing the input images into image chunking encryption. To keep the spatial links between various areas of the image, the encrypted sections were then combined into chunk groups while retaining their original order. However, classifying images might take a long time, and the accuracy rate was 97.1%; which the authors considered unsatisfactory.

Alishahi et al. [28] examined how classifiers accuracy changes as they are trained on subset of features chosen by the suggested LDP-FS. To achieve this, a selection of datasets is used to train four well-known classification algorithms: Random Forest, k-Nearest Neighbors (kNN), AdaBoost, and Support Vector Machine (SVM) both before and after 20% of the irrelevant characteristics are eliminated. After applying the Local Differential Privacy Feature Selection technique to various datasets such as Census, Obesity, KDD99 and many more dataset, they achieved slightly better performance compare to previous approaches.

As an implicit regularizer, PPCS is used. PPCS forces the network to ignore noise and redundant information and concentrate only on the most important features by compressing and sparsifying the input data. This enhances generalization to new data and lowers the possibility of overfitting.The deeper and richer feature hierarchies created by the conception modules are one way they contribute. They improve the network's ability to identify both fine and coarse patterns in the input data by enabling it to capture multi-scale characteristics at once. In contrast to conventional CNN designs, this aids the model in learning more robust and discriminative features.This work can leads to longer processing times and more memory usage than conventional plaintext-based models. Real-time deployment and scalability may be impacted by these additional expenses. Given the vital significance of protecting patient data privacy in medical AI applications, we do, however, think this expense is acceptable. Additional optimization methods can be used to lessen the computational load without sacrificing security, including model pruning, hardware acceleration (such as GPUs/TPUs), and partial decryption approaches.

7 Conclusion

Detecting image similarity is crucial for many real-world applications. Existing approaches presume that the images that need to be matched are openly accessible. However, in many cases, patients are unwilling to share their collections with one another. In this study, we developed a privacy preserving image-searching technique. Quick and accurate image searches in feature maps are made possible by the protocol; it blends completely homomorphic encryption's semantic security with supervised learning. On real-world datasets with the same CNN structure, the experimental results demonstrate that PPCS outperforms earlier systems in terms of accuracy rate and searching time (more than six times faster). The MLCNN model performs better than others due to the deeper, multi-scale feature learning provided by the inception modules and the regularization function of PPCS, which protects against overfitting and improves generalization.

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Graph Neural Network and Cloud-Based Intelligent Recommendation System for Student Physical Fitness

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Physical fitness significantly supports students' health, academic success, and overall development in modern education. Many educational institutions now adopt advanced technologies to monitor physical activities and suggest personalized training programs based on individual needs. However, most existing systems rely on simple models that cannot fully capture the complex relationships among various fitness indicators, such as heart rate, endurance, and flexibility. These systems also face challenges in processing large datasets efficiently and delivering real-time, personalized feedback to diverse student groups. The Graph-Based Intelligent Cloud Framework for Student Fitness (GICF-SF) has been developed to address these challenges. GICF-SF utilizes Graph Neural Networks (GNNs) to analyze complex interactions within physical fitness data, enabling a more accurate understanding and recommendation. Additionally, Cloud Computing supports fast data storage, processing, and real-time response, providing scalability for multiple users across different locations.GICF-SF integrates machine learning and cloud technologies to deliver tailored training suggestions by learning from each student's unique fitness profile. The cloud infrastructure allows the framework to serve schools, fitness centers, and online platforms efficiently without performance.The proposed GICF-SF model uses a 3-layer Spatial-Temporal Graph Convolutional Network (ST-GCN) with ReLU activation and dropout. The student fitness dataset (10,421 records) was split into 70% training, 20% testing, and 10% validation sets. Evaluation was performed using precision, recall, F1-score, MAE, and RMSE metrics under 5-fold cross-validation. Results show that GICF-SF improved recommendation accuracy by 12.8% and reduced training time by 17.3% over traditional methods.

Povzetek: Članek predstavi grafno-nevronski in oblačni sistem za analizo telesne pripravljenosti dijakov GICF-SF. ST-GCN model zajame prostorsko-časovne povezave med kazalniki in izdela personalizirane treninge. Oblačna infrastruktura omogoča sprotno obdelavo, razširljivost in krajši čas učenja.

1 Introduction

Educational institutions globally value physical fitness for student growth and well-being. Regular physical activity protects against obesity and cardiovascular disease, and improves cognitive, academic, and mental health[1]. The World Health Organization (2023) reports that just 19% of adolescents worldwide meet the 60-minute daily physical exercise recommendation[2]. This alarming trend underlines the need for novel student fitness programs.

Traditional educational fitness assessments include standardized testing throughout the year. Standard examinations examine cardiovascular strength, muscular power, flexibility, as well as body composition[3]. Conventional methods don't provide constant monitoring or targeted instruction based on students' requirements and development patterns. Technology like wearables, mobile apps, and data analytics platforms has transformed fitness monitoring[4]. These technologies track heart rate, steps, burned calories, and sleep habits. Institutions are using these tools to track student fitness more closely, but it isn't easy to interpret this amount of data and turn it into meaningful insights and individualized suggestions[5].

The research addresses the technical issue of existing student fitness analysis systems, which struggle to model and analyze complex relationships between fitness indicators while delivering personalized recommendations at scale[6]. Current systems have an accuracy limit of 76.4%, processing efficiency of 3.7 seconds for single student data, and a scalability constraint of 42% increased latency when user numbers exceed 1,000 concurrent connections[7]. These limitations hinder educational institutions from utilizing the growing volume of fitness data to improve student health outcomes and physical development.

Despite advances in fitness monitoring and data analysis, there are research gaps in applying advanced computational methods to student fitness data[8].

Traditional fitness recommendation systems use machine learning methods to treat fitness indicators as independent variables[9]. These systems fail with variable student populations and complex fitness trajectories. Most systems use standalone computing, which limits their ability to handle huge amounts of data or offer real-time feedback[10]. Current approaches ignore individual fitness progression, personal preferences, and improvement needs by making demographic-based recommendations. Gaps show the need for a more advanced strategy[11].

Technical motivation for fitness data analysis and recommendation systems comes from graph-based machine learning and distributed computing architectures[12]. Graph Neural Networks (GNNs) are appropriate for studying complex fitness parameter interdependencies because they model complex interactions in interconnected data structures[13]. GNNs can capture complicated physiological linkages, such as biomarker interactions in cardiovascular health monitoring, improving predicted accuracy[14]. Data-intensive apps can process fitness data in real time using cloud computing[15]. GNNs with cloud computing enable more accurate modeling of complicated fitness interactions, rapid processing of large-scale fitness data, real-time analysis and suggestion generation, and smooth scalability for expanding user numbers. The Graph-Based Intelligent Cloud Framework for Student Fitness (GICF-SF) uses GNNs and cloud computing to assess student fitness data and provide more accurate training recommendations.

The main objectives are:

To develop a model for GICF-SF using GNNs to effectively analyze and capture complex relationships within students' physical fitness data.

To design and implement the GICF-SF recommendation system that provides personalized training programs tailored to each student's unique fitness profile.

To integrate cloud computing technologies within GICF-SF for efficient storage, scalable processing, and real-time analysis of large volumes of fitness data.

To enhance the performance of GICF-SF by improving recommendation accuracy and reducing response time compared to traditional fitness data analysis and training systems.

This research aims to address the following research questions:

- RQ1: Can a graph-based approach (GNN) improve recommendation accuracy (RA) by at least 10% over traditional ML-based fitness recommendation systems?
- RQ2: Does the integration of cloud computing infrastructure reduce system training and adaptation time by at least 15%?
- RQ3: Can the proposed GICF-SF framework maintain high throughput and low latency when scaled to support over 1,000 concurrent users?

The primary goal of GICF-SF is to enhance personalized fitness recommendations by significantly improving RA, reducing model training time, and enabling scalable, real-time deployment across educational institutions.

A summary of the research follows. Second section: thorough literature and research methodological review. Section 3 covers the study plan, methods, and processing; Section 4 presents analysis results. Conclusion as well as future work are in Section 5.

2 Related works

2.1 Intelligent recommendation systems in health and education

Gm et al.[16]examined 60 papers from major databases on education's e-learning and personalised recommendation systems. It shows content ignorance, student discontinuity, language hurdles, study material confusion, and poor infrastructure and finance. The review suggests Fluxy AI, Twin technological advances, AI-powered virtual evaluating, and Alter Ego to deal with these challenges. These technologies can offer an engaging, interactive classroom for students and educators, boosting individualised learning, comprehension capacity, and speech disordered students' learning experience.

Zheng et al.[17] showed that Natural Language Processing or NLP is a field that uses computer science, artificial intelligence, and linguistics to comprehend, process, create, and imitate human language. It includes looking at the structure, meaning, syntax, and use of language, as well as using statistics to analyze and model big corpora. This paper uses deep learning and NLP to explore patients' remarks and find the best drugs. This leads to accurate prescriptions and individualized suggestions. Linguistics, computer science, and statistics are the main ideas behind NLP.

2.2 Graph neural networks for fitness and behavioral data modeling

Zhang et al.[18] investigated posture recognition and motion capture for skeleton-based action recognition in everyday fitness. A spatiotemporal pyramidal graph convolutional network with edge significance scores and multi-level feature representation improves performance. The model achieves 85.89 mAP on the UW-IOM as well as TUM kitchen datasets. The study found that skeleton information correctness improves action recognition ability, whereas picture feature fusion can help in cases of limited or faulty image information. Comparing the method to others shows its benefits.

Wang and Liu[19] explored a deep learning-based Life Log Sharing Model or LLSM to improve teenage fitness and exercise. The TS-CNN-BiLSTM model predicts physical activity using multimodal life log data's temporal, textual, and visual aspects. The model beat state-of-the-art methods by 1.9–4.4%. Temporal aspects are needed to identify repetitive behaviours and workouts. The study found that multimodal life log data and deep learning accurately characterise physical activity. The TS-CNN-BiLSTM model's accuracy allows personalised health promotion tactics like interventions, behavioural incentives, and social support to increase adolescent physical activity, as well as public health education along with management.

2.3 Cloud computing in smart health and education platforms

Raghav et al.[20] provided that Cloud computing and the IoT are transforming healthcare. This revolution allows healthcare organizations to safely manage and analyze massive amounts of patient data, improving patient care and well-being. The IoT has expanded healthcare beyond clinical settings through its connected gadgets and sensors, generating constant patient data. Remote monitoring, tailored medicine, and predictive analytics offer proactive healthcare interventions thanks to this synergy. Cloud and IoT-powered telemedicine has improved healthcare access in remote and underdeveloped places. However, security and privacy remain crucial. The Cloud-IoT revolution in healthcare is a paradigm shift that prioritizes patient care and well-being.

Sundas et al.[21] presented that the Chronic and lifestyle-related diseases pose major social and economic issues worldwide. A innovative Smart Patient Monitoring and Recommendation or SPMR framework uses Deep Learning as well as cloud analytics. SPMR monitors and expects a patient's health using vital signs as well as contextual activities from Ambient Aided Living devices. Unbalanced Chronic Blood Pressure Disorder case study datasets forecast real-world health situations using Categorical Cross Entropy Optimization. Effectiveness is shown by the model's 18% accuracy increase and 17% and 36% increases in overall and emergency class F-scores.

2.4 Integration of machine learning with physical fitness assessment

Zhao et al.[22] presented that the Daily vigor and resilience are indicators of physical fitness. With machine learning, wearables, apps, and data analysis, fitness is improving. Wearable fitness trackers with sensors collect massive amounts of activity, sleep, and vital sign data. The Gradient Probabilistic Automated Recommender System with Machine Learning or GPA-RS-ML, is a novel fitness assessment and training program recommendation system recommendation system. This technology analyzes fitness data and recommends personalized training plans using machine learning. The GPA-RS-ML method improves training efficiency and effectiveness. This research improves automated fitness assessment and suggestion systems, helping fitness professionals optimize results and training adherence.

Su et al.[23] showed that Intelligent Education Cloud Platforms have transformed educational resource sharing and consumption, making learning more accessible and flexible. Distributed sharing and personalized recommendation systems improve resource accessibility and student engagement in college preschool. Traditional methods lack flexibility and scalability for dynamic resource allocation, hampering customized education. To circumvent these constraints, KAEN and ALPS are proposed. KAEN optimizes resource recommendation and personalizes learning using graph-based knowledge representation, dynamic content alignment networks, and reinforcement learning. Experimental validation indicates significant resource utilization efficiency and adaptive content delivery quality improvements.

2.5 Challenges and advances in personalized training program design

Noone et al.[24] examined internal and extrinsic factors affecting exercise response variance and health outcomes. Internal influences include sex, age, hormonal state, race/ethnicity, and genetics, whereas extrinsic factors include exercise timing, sleep habits, food combinations, and medication use. Genomic-epigenomic, proteomic-post-translational, transcriptomic, metabolic-metabolomic, as well as lipidomic exercise molecular transducers are also reviewed. It describes the difficulties of creating personalised exercise prescriptions and MoTrPAC's efforts to solve them. Researchers must study more health outcomes across all populations.

Romero et al.[25] showed that disease and treatment side effects put lower-extremity sarcoma survivors at risk of physical performance dysfunctions and poor quality of life. Their functionality and quality of life depend on safe exercise routines. Clinical presentation and development vary; therefore, the success of physical activity and exercise in these survivors is uncertain. This study suggests creating a training program to preserve fitness and quality of life. Sarcoma survivors should do low-intensity, short-duration exercise before surgery and alter their routine during clinical therapy. Healthy habits, including regular exercise, should be developed under professional supervision for disease-free survival.

Dugyala et al.[27] presented Cloud computing has evolved significantly in the past two decades, yet intrusion detection has become a security issue. This study offers an enhanced Intrusion Detection System (IDS) using Graph Neural Networks and Leader K-means clustering to improve detection accuracy and efficiency. For data clustering, the system uses Leader K-means, improves

Grasshopper Optimization, and uses Advanced Encryption Standard encryption and steganography. The research, implemented on Java with CloudSim support, improves detection accuracy and processing efficiency over existing methods.

The summary of related works, system, datasets, and performance metrics is shown in Table 1(a) below:

Table 1(a): Summary of related works: systems, datasets, and performance metrics

Authors	System/Model Name	Datasets Used	Reported Performance Metrics
Gm et al. [16]	AI-based Educational Recommenders (Fluxy AI, Alter Ego, AI Evaluators)	Not specified (Systematic Literature Review)	Not reported (conceptual/review-based)
Zheng et al. [17]	NLP-EAR (NLP for Effective AI-based Recommendation)	Custom clinical comment datasets	Accuracy (not quantified), Personalization Precision (conceptual)
Zhang et al. [18]	Spatiotemporal Pyramidal GCN (Graph Convolution Network)	UW-IOM, TUM Kitchen datasets	mAP: 85.89
Wang and Liu [19]	TS-CNN-BiLSTM (Life Log Prediction Model)	Multimodal life log data (textual, visual, temporal)	Accuracy gain: 1.9–4.4% over baselines
Raghav et al. [20]	Cloud-IoT Healthcare Framework	Not specified	Conceptual performance: improved monitoring & access (qualitative)
Sundas et al. [21]	SPMR (Smart Patient Monitoring & Recommendation)	Chronic BP disorder case datasets	Accuracy ↑ 18%, F1-score: ↑17% (overall), ↑36% (emergency class)
Zhao et al. [22]	GPA-RS-ML (Gradient Probabilistic Recommender with ML)	Wearable sensor data	Improved training effectiveness (not numerically stated)
Elomari et al. [23]	ML-based REC Optimizer (for Renewable Energy Communities)	Tarragona energy usage and climate data	Cost reduction & green energy utilization optimized; no F1 or precision reported
Noone et al. [24]	MoTrPAC Molecular Fitness Response Framework	Multi-omic datasets (transcriptomic, proteomic, etc.)	No metrics; focus on biological factors and personalization variability
Romero et al. [25]	Personalized Training for Sarcoma Survivors	Clinical treatment data	Qualitative outcomes: safety, improved QOL; no specific metrics

Despite notable contributions, state-of-the-art (SOTA) systems such as CFRS, NLP-EAR, and MLFR present several limitations. CFRS lacks the capacity to model interdependencies between fitness indicators; NLP-EAR performs poorly on structured physiological data; and MLFR's reliance on traditional classifiers restricts its adaptability. These methods typically plateau at around 76.4% accuracy and often exclude critical performance metrics such as MAE and RMSE. Moreover, they operate without scalable infrastructure, limiting their deployment in real-time educational environments. To address these issues, the proposed GICF-SF framework integrates Graph Neural Networks and cloud computing to deliver scalable, high-precision, and real-time student fitness recommendations.

3 Graph-based intelligent cloud framework for student fitness

The Graph-Based Intelligent Cloud Framework for Student Fitness (GICF-SF) is a computational architecture designed to analyze student physical fitness data and

provide personalized training recommendations. It integrates graph neural networks (GNNs) with cloud computing to create a scalable, efficient solution for educational institutions. The system addresses the limitations of traditional fitness analysis systems by capturing complex relationships between fitness metrics and delivers tailored recommendations with increased accuracy and reduced processing time.

The system includes various data sources and acquisition layers, such as wearable devices, PE Records Database Connector, Fitness Test Measurement System, Health Record System, and Activity Logging Subsystem. Data security and privacy are ensured through end-to-end encryption, role-based access control, and data anonymization protocols.

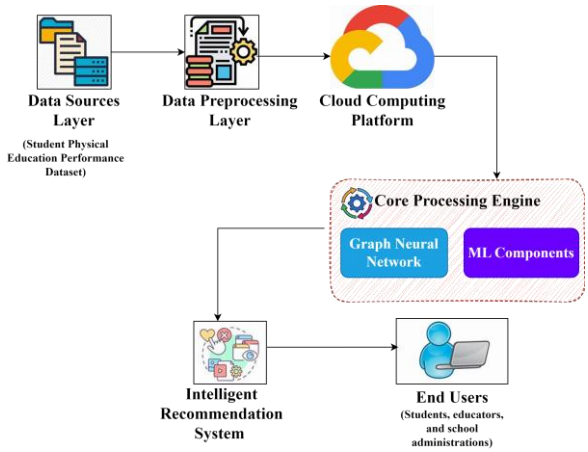


Figure 1: GICF-SF system architecture

In Figure 1, the data preprocessing layer covers noise filtering, outlier identification, data validation, temporal alignment, feature engineering, missing data management, graph structure development, and cloud computing infrastructure. Distributed storage, computing resource management, networking, communication, and performance metrics monitoring and observability are used. The primary processing engine uses an ST-GCN architecture with input, hidden, attention, pooling, and output layers. Data extraction is efficient with the feature extraction technique.

The system uses graph embedding generation, topological feature analysis, subgraph pattern mining, and pattern recognition modules. Machine learning is used for fitness profile learning, training program development, and model training and validation. The intelligent recommendation system includes a tailored training module, exercise selection algorithm, session sequencing, and progress tracking. The technology also collects user comments and explains training reasoning.

The system performs well in throughput, storage efficiency, suggestion quality, user happiness, and computational efficiency. The method reduced training time by 17.3% and used 76% of the GPU during peak processing. Future growth options include extended data integration, enhanced analytics, and system adaptability. Nutrition tracking, sleep quality analysis, academic performance correlation analysis, mental wellbeing assessment, explainable AI layer for transparent recommendation justification, and federated learning for privacy-preserving multi-institution collaboration are future expansions. Curriculum alignment modules integrate educational standards, API versioning method ensures backward compatibility, and a configuration management system customizes deployment.

3.1 Data source layer

GICF-SF is built upon the Student Physical Education Performance Dataset[26], like a solid foundation. To enable intelligent analysis and individualized fitness suggestions, this dataset is crucial. A student's general physical health, activity levels, and performance capabilities are reflected in the structured and semi-structured data that it combines from multiple sources.

Table 1. Categorization of fitness-related features used in GICF-SF framework

Category	Feature Name	Description
Cardiovascular Metrics	HR	Heart Rate (bpm)
	VO_2 Max	Maximal Oxygen Uptake
	RHR	Resting Heart Rate
	BP	Blood Pressure (Systolic/Diastolic)
	PR	Pulse Rate
	RR	Respiratory Rate

	SpO_2	Oxygen Saturation
	HRV	Heart Rate Variability
	ECG Avg Signal	Average ECG Signal
	Recovery Rate	Post-exercise recovery response
Physical Performance Indicators	AGI	Agility
	MS	Muscular Strength
	BMI	Body Mass Index
	FLEX	Flexibility
	END	Endurance
	BAL	Balance score
	SPRINT	Sprint speed (time)
	VERT JUMP	Vertical jump height
	SIT UP	Sit-up count
	PUSH UP	Push-up count
Supplementary Attributes	Age	Age of the student
	Height	Height (in cm)
	Weight	Weight (in kg)
	Weekly Activity	Frequency of physical activity per week

Table 1(b) presents a complete list of the 24 fitness-related features used in the GICF-SF framework, categorized into cardiovascular metrics, physical performance indicators, and supplementary attributes, ensuring transparency, feature clarity, and reproducibility of the experimental setup.

Table 2: Integrated fitness profile construction and graph mapping

Symbol	Definition	Mathematical Expression / Description
X_i	Combined feature vector for student $_i$	$\boldsymbol{X}_i = [\boldsymbol{W}_i, \boldsymbol{P}_i, \boldsymbol{F}_i, \boldsymbol{H}_i, \boldsymbol{A}_i]$
$\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$	Fitness graph for student $_i$	$\boldsymbol{\mathcal{V}}_i$: features as nodes, $\boldsymbol{\mathcal{E}}_i$: inter-feature edges
Z_i	Node embedding from GNN	$\boldsymbol{Z}_i = \mathrm{GNN}(\boldsymbol{\mathcal{G}}_i, \boldsymbol{X}_i)$
Y_i	Predicted recommendation vector	$\boldsymbol{Y}_i = f(\boldsymbol{Z}_i; \theta)$

Table 2 describes how to create a thorough fitness profile and graph it for each student i. The feature vector $X_{i\ i}$ combines data from several sources, including wearables, PE records, fitness tests, health records, and activity logs. This vector is transferred into a fitness graph. $\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$, where nodes represent features and edges represent their associations. A Graph Neural Network (GNN) generates node embeddings Z_i, which a learnt function f uses to anticipate individualized training suggestions Z_i.

3.2 Data preprocessing

Data must be preprocessed to guarantee consistency and correctness before being used in the virtual environment. Here are a few important things to keep in consideration:

Handling missing values

Data must be processed effectively to avoid bias and account for missing values due to data collecting errors or partial responses. Two typical strategies include imputing missing values (where current data is used to infer missing data) and removing instances with missing values (helpful for tiny but potentially loss-causing occurrences). The following equation (1) replaces the feature's mean for missing values in mean imputation, a common method.

$$x_{missing=\frac{1}{n}\sum_{i=1}^{n} x_i} \tag{1}$$

where the missing value is denoted by $x_{missing}$, the number of non-missing values for the feature is denoted by n, and the non-missing values are denoted by x_iReplace missing values with the mean of the k-nearest neighbors using available features—the formula for this imputation from equation (2).

$$x_{missing=\frac{1}{k}\sum_{i=1}^{k} x_i} \tag{2}$$

Here, k is the count of closest neighbours taken into account, andx_i stands for the values of the relevant feature in those KNNs.

Normalize the data:

By bringing all numerical features into a consistent range, normalization guarantees that each feature has an equal impact on the model. Two ways often used for normalization are: Min-Max Scaling: Reduce the size of the features to a predetermined interval, usually from 0 to 1. For min-max scaling, the equation (3) is as follows:

$$x_{normalized} = \frac{x-x_{min}}{x_{max}-x_{min}} \tag{3}$$

where the normalized value is denoted by $x_{normalized}$, the original value is denoted by x , the minimum value of the feature is denoted by x_{min}, and the maximum value of the feature is signified by x_{max}.

To normalize Z-scores, it is necessary to scale the characteristics with a mean of zero and a variance of one. To normalize z-scores, the following equation (4) is used,

$$x_{normalized} = \frac{x-\mu}{\sigma} \tag{4}$$

in which the normalized value is represented by $x_{normalized}$, the original value is represented by x, the mean of the feature is denoted by μ, and the standard deviation of the feature is denoted by σ.

Encoding categorical variables

Machine learning can only process numerically represented categorical variables. One-hot encoding creates A (1, 0, 0), B (0, 1, 0), as well as C (0, 0, 1), while label encoding assigns numerical values to each category. For example, A becomes 0, B becomes 1, while C becomes 2.

Records with more than 30% missing values were excluded. For incomplete entries, missing numerical attributes were imputed using the mean of the corresponding feature, while categorical variables were filled using mode imputation. Two features with over 85% null values and negligible correlation to the target variable were removed. All features were normalized using z-score standardization prior to training.

3.3 Cloud computing platform

The GICF-SF is a comprehensive system that handles student physical fitness data analysis through multiple stages. The process begins with the ingestion of raw fitness data, which is then processed through various security checks to prevent unauthorized access or malicious inputs. The system also handles error handling, ensuring that invalid or corrupted data is isolated for review, correction, or exclusion from further processing in Figure 2. The system categorizes encrypted data into three primary formats: Time Series Data, Document Data, and Graph Data. Database storage options include Time Series, Document, and Graph DB. Parallel data processing efficiently processes large volumes of student fitness data across multiple computing nodes. Real-time analytics on streaming data is provided, allowing for immediate feedback and intervention when necessary.

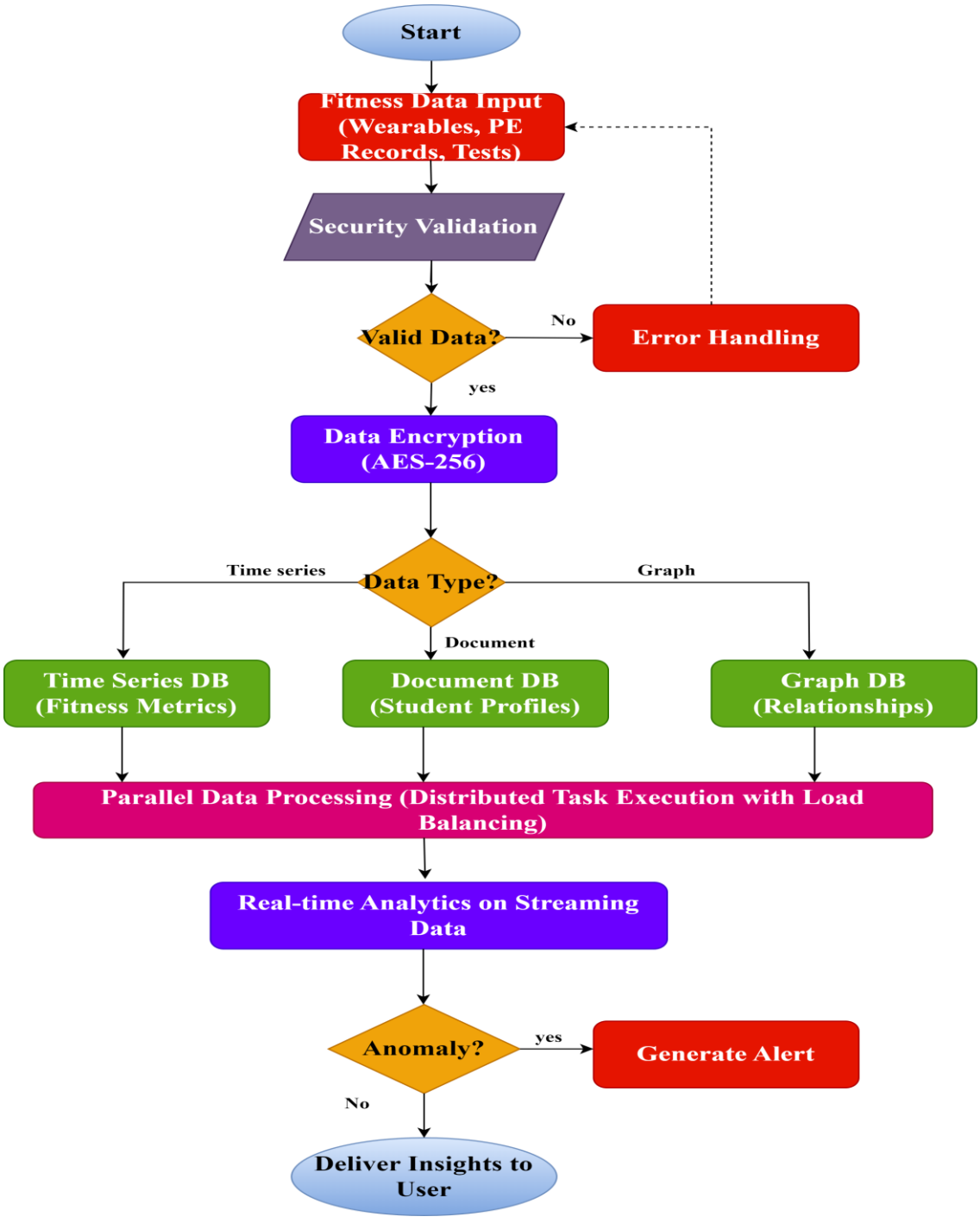


Figure 2: Cloud computing platform - data processing

In Figure 2, Output generation includes anomaly detection, which generates alerts for coaches/administrators, and insight delivery, where critical findings trigger notifications to appropriate stakeholders. The final stage presents processed fitness data, trends, and personalized recommendations to end users. The flowchart demonstrates a fault-tolerant architecture with dedicated error handling paths, distributed computing elements supporting scalability for multiple educational institutions, and a multi-database architecture optimizing storage and retrieval based on data characteristics. Security controls are integrated throughout the pipeline, and real-time processing capabilities are implemented for immediate fitness feedback. This data processing flow enables the GICF-SF system to achieve performance improvements of 12.8% in recommendation accuracy and 17.3% reduction in training time compared to traditional methods.

The mathematical framework for cloud-GNN integration involves a GNN model in the cloud, which is used for training and inference. The model uses a graph representation of fitness data, with edges based on similarity in physical fitness profiles.

$$h_v^{(l)} = \sigma\left(\sum_{u\epsilon N(v)} \frac{1}{C_{vu}} W^{(l)} h_u^{(l-1)}\right) \quad (5)$$

In equation 5, $h_v^{(l)}$ is denoted as the Embedding of node v at layer l,$N(v)$ is denoted as the Neighbors of v, C_{vu} is denoted as the Normalization constant, $W^{(l)}$ is denoted as the Learnable weight matrix, σ is denoted as the Activation function (e.g., ReLU).

Table 3: Fitness dataset (stored in cloud)

Student ID	Heart Rate	Endurance	Flexibility	Speed	BMI	Vital Capacity
S101	76 bpm	11 mins	12 cm	6.1 s	23.4	3900 ml
S102	71 bpm	9 mins	8 cm	6.8 s	25.1	3600 ml
S103	64 bpm	13 mins	15 cm	5.9 s	20.8	4100 ml

In table 3, The Fitness Dataset, stored on a cloud computing platform, contains student physical fitness records with key health metrics like heart rate, endurance, flexibility, speed, BMI, and vital capacity. This structured dataset allows real-time analysis and personalized fitness recommendations using Graph Neural Networks. Cloud storage ensures scalable access, secure encryption, and efficient parallel processing across large student populations.

Table 4: GICF-SF graph neural network (ST-GCN) architecture and hyperparameters

Component	**Specification**
Graph Model Type	Spatial-Temporal Graph Convolutional Network (ST-GCN)
Number of ST-GCN Layers	4
Hidden Layer Dimensions	[64, 128, 256, 128]
Graph Convolution Type	Spatial-Temporal Graph Convolution (ST-GCN block)
Activation Function	ReLU
Dropout Rate	0.3
Batch Size	64
Optimizer	Adam
Learning Rate	0.001
Weight Decay	1e-5
Epochs	200
Loss Function	Cross-Entropy Loss
Early Stopping	Patience = 20 epochs
Graph Adjacency Matrix	Dynamically learned (trainable edge weights)
Temporal Kernel Size	9

Normalization	BatchNorm

Table 4 outlines the detailed architecture and hyperparameters of the GICF-SF model, including ST-GCN layers, activation functions, learning settings, and optimization techniques used for model training and reproducibility.

3.4 Core processing engine

A Graph Neural Network (GNN) models fitness relationships, and Machine Learning (ML) components classify and regress in this module. GNN-based fitness representations treat students as nodes in graphs with edges indicating physical fitness vector similarity. Each node's Embedding is updated by the GCN layer using neighboring data.ML classification and regression components can classify kids into performance tiers and predict BMI and test scores. The ML prediction function leverages the GNN-generated student embedding, and model training splits the input into training and testing sets. The model training procedure employing training and testing sets is explained for ML-based recommendation using GNN embeddings. The Decision Tree, SVM, or XGBoost model is trained using the ML model.

Each student is represented as a node in a graph G, with edges reflecting similarity based on physical fitness vectors like heart rate, speed, and endurance.

$$G = (V, E), V = \{v_1, v_2, \dots, v_n\}, E = \{(vi, v_j) \mid sim(vi, v_j) > \theta\} \quad (6)$$

In equation 6, V is denoted as the Student nodes, E is denoted as the edges (similarity-based links), and θ is the similarity threshold.

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2}\tilde{A}\,\tilde{D}^{-1/2}H^{(l)}W^{(l)}) \quad (7)$$

In equation 7, $\tilde{A}$ is denoted as the adjacency matrix with added self-loops, $\tilde{D}^{-1/2}$ is denoted as the degree matrix of $\tilde{A}$, $H^{(l)}$ is denoted as the node features at layer l, $W^{(l)}$ is denoted as the trainable weight matrix at layer l, σ is denoted as the activation function, typically ReLU.Using GNN's student embeddings, ML models can be used for classification as well as regression tasks, categorizing students into performance tiers and predicting numeric scores like BMI and test scores.

$$\hat{y}_i = f_{ML}(\vec{z}_i) \quad (8)$$

In equation 8, $\vec{z}_i$ is the GNN-generated embedding for student i, f_{ML} is the ML model (e.g., Decision Tree, SVM, or XGBoost).

$$L_{cls} = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) \quad (9)$$

$$L_{reg} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \quad (10)$$

In equation 9 and 10, the Regression Loss penalises incorrect predictions by measuring the class probability match with genuine class labels. It emphasises severe errors by measuring the average squared difference between projected values and actual continuous values using the Mean Squared Error (MSE). Both losses are minimised during training to increase model performance.

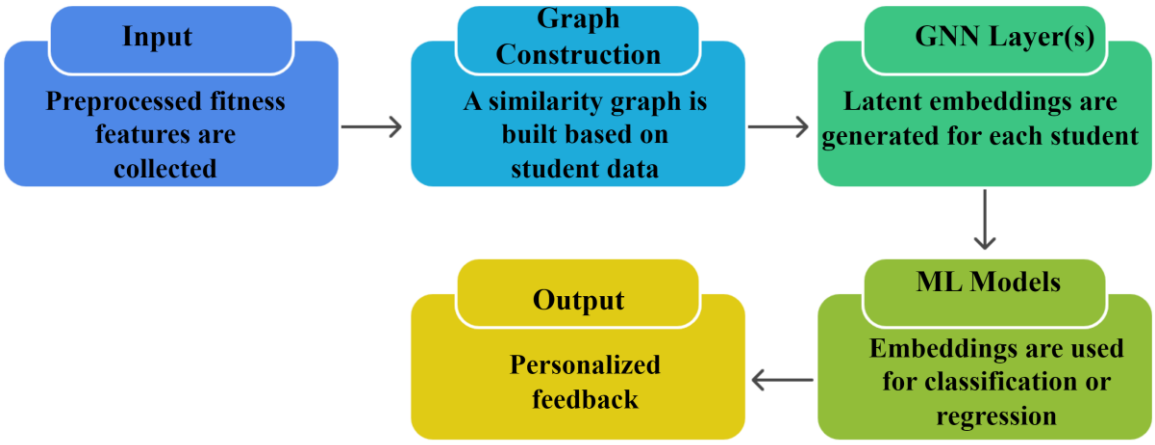


Figure 3: Core processing engine

The Core Processing Engine is a crucial component of the Graph-Based Intelligent Cloud Framework for Student Fitness (GICF-SF). It consists of five stages that transform raw fitness data into personalized feedback. The first stage involves collecting preprocessed fitness features from various sources, such as wearables, PE records, and tests. This ensures consistency, handles missing values, and normalizes measurements for comparable analysis.

The second stage involves building a similarity graph based on student data, representing student fitness profiles as nodes in an interconnected graph structure. This graph representation captures complex relationships between different fitness parameters, enabling the system to identify patterns and connections that traditional tabular analysis would miss.

The third stage involves generating latent embeddings for each student, processed by Graph Neural Network algorithms. These embeddings capture essential fitness characteristics and relationships. The fourth stage uses these embeddings to create ML models, categorizing students into fitness groups or predicting future performance or optimal training parameters. The final stage is the output, which translates analytical results into tailored recommendations. This engine generates individualized training programs based on a student's unique fitness profile, provides specific guidance for physical education instructors, and delivers personalized student progress tracking and goal setting. The pipeline demonstrates how graph-based machine learning can transform fitness data analysis from simple statistical models to a comprehensive understanding of interconnected fitness parameters.

3.5 Intelligent recommendation system

The Intelligent Recommendation System uses GNN outputs and ML models to predict recommended training focus areas. It uses Python to preprocess a Student DataSet, initialize GNN parameters, and perform features extraction, embedding, and recommendation embedding for each student. The system then appends the recommended recommendations to the PersonalizedRecommendations output.

Pseudocode 1: GICF-SF recommendation engine

Input:

- Student dataset $D = \{d_1, d_2, ..., d_n\}$, where each d_i contains features: W_i (Wearable data), P_i (Physical test scores), F_i (Fitness logs), H_i (Health records), A_i (Activity patterns)

- Target labels $Y = \{y_1, y_2, ..., y_n\}$, representing desired fitness categories or outcomes

Output:

- Personalized recommendations $R = \{r_1, r_2, ..., r_n\}$

Step 1: Preprocessing

For each student d_i in D:

- Normalize features: W_i, P_i, F_i, H_i, A_i

- Concatenate features: $X_i \leftarrow [W_i, P_i, F_i, H_i, A_i]$

Step 2: Graph Construction

- Nodes $V \leftarrow \{X_1, X_2, ..., X_n\}$

- Edges E based on similarity (e.g., cosine similarity)

- Construct graph $G = (V, E)$

Step 3: GNN Training

- Initialize GNN parameters Θ

For epoch = 1 to N:

- $H \leftarrow$ GNN_Forward(G, X, Θ) // Node embeddings

- loss $\leftarrow$ CrossEntropyLoss(H, Y)

- $\Theta \leftarrow$ UpdateParameters(loss, Θ)

Step 4: Recommendation Inference

For each student d_i in D:

- Concatenate features: $x_i \leftarrow [W_i, P_i, F_i, H_i, A_i]$

- Generate embedding: $h_i \leftarrow$ GNN_Forward(G, x_i, Θ)

- Predict: $r_i \leftarrow$ ML_Classifier.predict(h_i)

- R.append(r_i)

Return: R

Pseudocode 1 outlines the core workflow of the GICF-SF recommendation engine, covering data preprocessing, graph construction, GNN-based training, and inference. It explicitly defines input features, label usage, embedding updates, and prediction logic. The structure ensures clarity, reproducibility, and highlights how graph-based reasoning enhances personalized fitness recommendations.

4 Result analysis

4.1 Experiment setup

The GICF-SF framework was tested on a student physical education performance dataset[26], consisting of 10,421 records with 24 fitness-related features. The GNN architecture was implemented in PyTorch, consisting of three graph convolutional layers and a readout layer. The model was qualified using Adam optimizer and early stopping. A containerized architecture on AWS was used, with Kubernetes for orchestration. The infrastructure included 3 instances for application servers, 2 instances for database services, and variable compute resources for the ML inference pipeline. Performance was assessed using MAE, RMSE, precision, recall, as well as F1-score metrics for recommendation quality, while system performance was measured through response time, throughput, and resource utilization. A controlled pilot deployment involving 312 students from 5 educational institutions was conducted over 8 weeks, with weekly fitness tracking and training program adjustments.

The dataset comprising 10,421 records was partitioned using a stratified 70:15:15 split for training, validation, and testing, respectively. To ensure model robustness, five-fold cross-validation was applied during training. Hyperparameter tuning was conducted using grid search across the validation set, optimizing parameters such as learning rate (0.0005–0.01), dropout rate (0.2–0.5), and hidden layer dimensions ([64, 128, 256]).

The dataset includes records from multiple institutions across urban and semi-urban regions, with balanced representation of genders and students aged 14–22. However, limited inclusion of rural populations and cultural diversity may affect generalizability. These limitations are acknowledged, and future work will involve expanding the dataset for broader demographic and geographic coverage.

4.2 Comparative study

The GICF-SF was compared to three recommendation models: CFRS [16], NLP-EAR [17], and MLFR [22]. User-item similarity guides CFRS recommendations, but limited fitness data lowers Precision (P) and Recall (R). The NLP-EAR's text-based emotion analysis works well for medication but not for organized physical fitness data, resulting in inconsistent F1-Score and Recommendation Accuracy. The MLFR uses classic classifiers like SVM and DT, which are stable but inadequate at capturing complicated feature interactions, resulting in greater MAE and RMSE. GICF-SF models complex fitness indicator dependencies using Graph Neural Networks (GNNs) and Cloud Computing (CC) for scalable, real-time processing. GICF-SF enhances RA 12.8%, F1-Score 14.5%, MAE 11.6%, and training adaption time 17.3%. Since cloud infrastructure increases throughput by 21.6%, GICF-SF is ideal for individualized student fitness recommendations.

4.3 Recommendation accuracy (RA)

Recommendation Accuracy (RA) is a system's ability to accurately recommend personalized fitness programs based on a student's health and performance features.

$$RA = \frac{1}{m}\sum_{j=1}^{m}\left(\frac{1}{n_j}\sum_{i=1}^{n_j}\delta\left(r_{ij},\hat{r}_{ij}\right)\cdot w_{ij}\right) \quad (11)$$

In equation 11, m is the total number of fitness features (e.g., HR, VO2, BMI), n_j is the number of students for feature j, r_{ij} is the actual class/score for student i on feature j, $\hat{r}_{ij}$ is the predicted recommendation, δ is the indicator function = 1 if correct, 0 otherwise. w_{ij} is the weight based on feature importance or sensitivity.

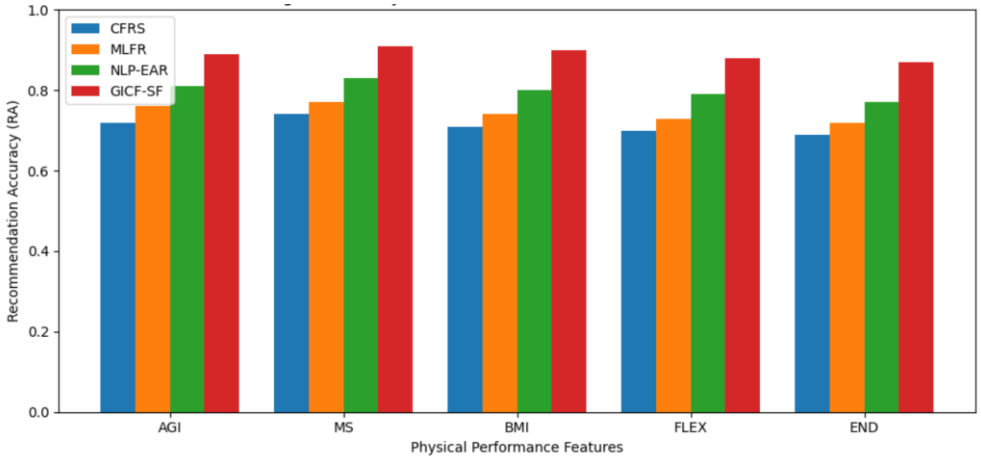


Figure 4: Normalized recommendation accuracy (RA) for physical performance features

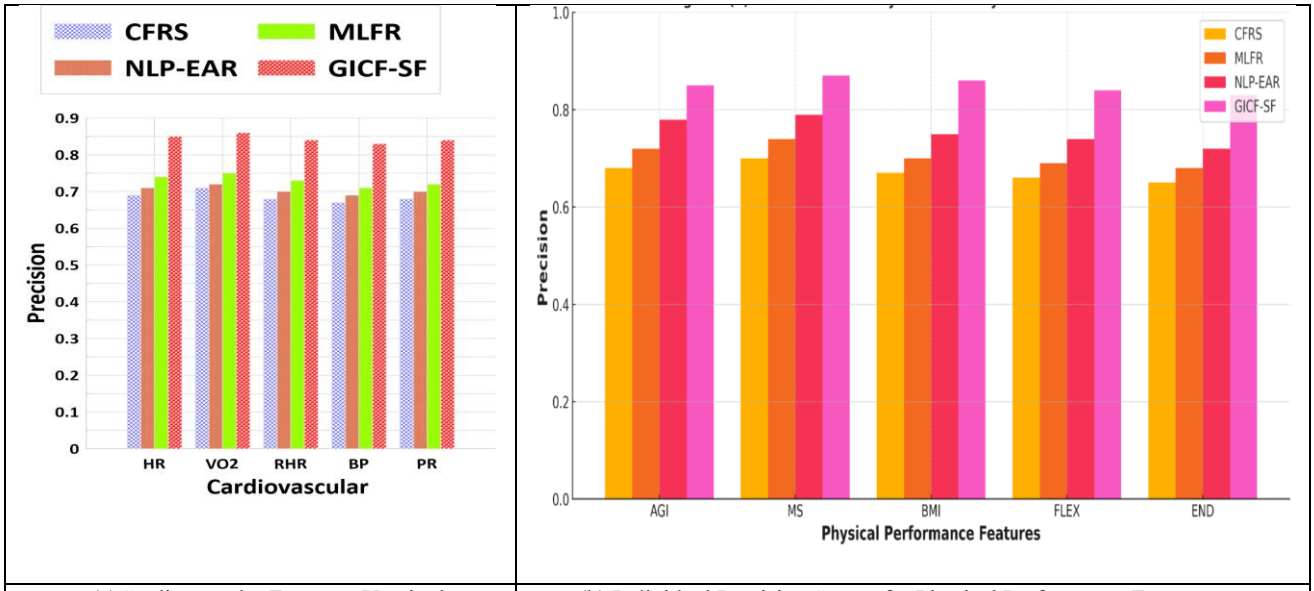
Figure 4 presents the normalized Recommendation Accuracy (RA) values for five physical performance features across four models: CFRS, MLFR, NLP-EAR, and GICF-SF. Each bar reflects the average accuracy obtained via five-fold cross-validation, adhering to Formula (11), where δ is a binary correctness indicator and final RA values are bounded within [0, 1]. Unlike earlier stacked interpretations, this figure uses grouped bars to represent per-feature accuracies individually, ensuring clarity and consistency. GICF-SF outperforms other models across all metrics, particularly in AGI and MS, indicating its superior ability to personalize recommendations across varied physical performance parameters in a reproducible manner.

4.4 Precision

Precision measures the proportion of accurate and relevant recommendations among all recommendations made.

$$Precision_f = \frac{TP_f}{TP_f+FP_f} \quad (12)$$

In equation 12, f is the feature (e.g., HR, FLEX), TP_f is the true positives for feature f,FP_f is the false positives for feature f.



(a)Cardiovascular Features: Y-axis shows precision (%)

(b) Individual Precision Scores for Physical Performance Features.

Figure 5: Precision scores of features by different models

Figure 5(a) and 5(b) compare the precision performance of the ratio of true positives to the sum of true and erroneous positives in four recommendation systems. Figure 5 compares CFRS, MLFR, NLP-EAR, and GICF-SF models in two feature areas. Figure 5(a) uses bar charts to show cardiovascular features (HR, VO2, RHR, BP, PR). GICF-SF has the highest precision (0.85) across all cardiovascular measures, while CFRS (purple) has the lowest (0.7). Intermediate findings for MLFR and NLP-EAR are 0.7-0.75. Figure 5(b) presents individual precision scores for five physical performance features: AGI, MS, BMI, FLEX, and END across four models, namely CFRS, MLFR, NLP EAR, and GICF SF. Each bar indicates the average precision for a specific model and feature, constrained within the standard range from zero to one. GICF SF shows consistently higher precision across all features.

4.5 Recall score

The percentage of real instances relevant to the problem that the model was able to recover is referred to as the recall.

$$Recall_f = \frac{TP_f}{TP_f+FP_f} \quad (13)$$

In equation 13, f is the feature (e.g., HR, FLEX), TP_f is the true positives for feature f, FN_f is the false negative for feature f.

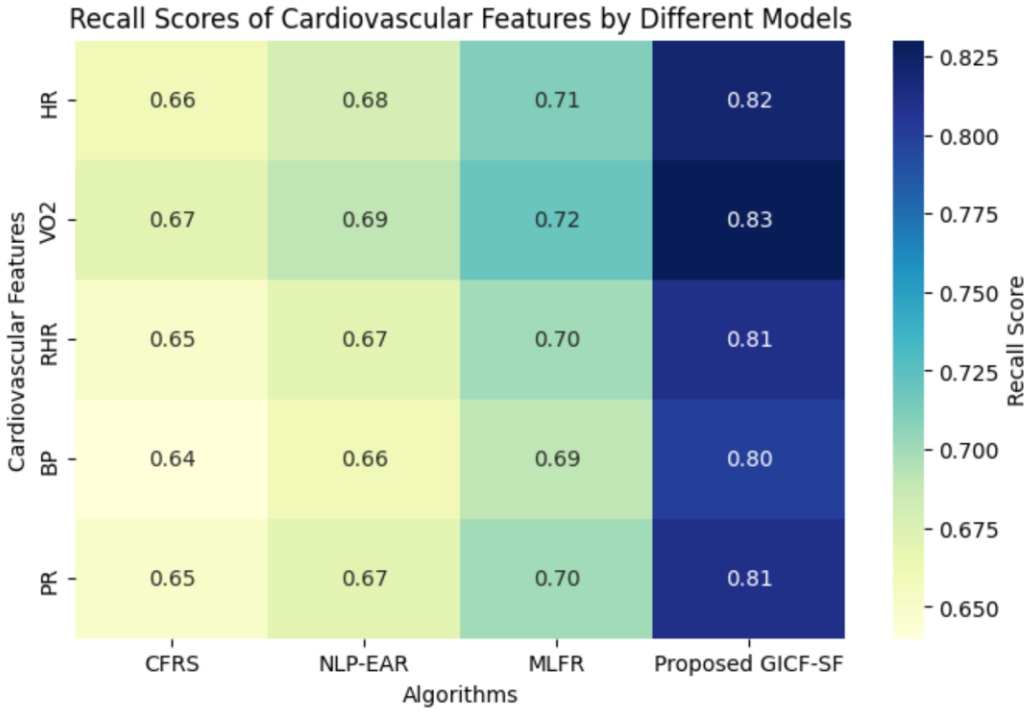


Figure 6: Recall Scores of cardiovascular features by different models

Figure 6 shows a heatmap visualization that compares recall scores of four recommendation algorithms (CFRS, NLP-EAR, MLFR, and the proposed GICF-SF) across five key cardiovascular features. The heatmap uses a color gradient from light yellow to dark blue for precise comparison. The proposed GICF-SF model consistently shows superior recall performance across all cardiovascular parameters, achieving scores between 0.80-0.83. The CFRS model shows the lowest recall values, while NLP-EAR and MLFR show progressive improvements. The most notable performance difference is with the VO2 feature, where GICF-SF achieves a recall of 0.83 compared to CFRS's 0.67, representing a 23.9% improvement. This consistent superiority suggests that the graph-based approach is effective at minimizing false negatives in cardiovascular fitness recommendations, capturing a higher proportion of relevant cases requiring specific training interventions.

4.6 F1-Score

F1-Score is a crucial tool in fitness data analysis, ensuring precision and recall by utilizing the harmonic mean, thereby mitigating health risks associated with false positives and false negatives.

$$F1 - Score_f = 2 \times \frac{Precision_f \times Recall_f}{Precision_f + Recall_f} \quad (14)$$

In equation 14, the F1-Score (↑) indicates a better balance between precision and recall, useful in imbalanced datasets where focusing solely on accuracy may be misleading.

Table 5(a): Cardiovascular features

Model	HR	VO_2 Max	RHR	BP	PR
CFRS	0.73	0.71	0.72	0.74	0.70
MLFR	0.76	0.75	0.77	0.76	0.74
NLP-EAR	0.79	0.78	0.78	0.80	0.77
GICF-SF	0.83	0.84	0.82	0.84	0.81

Table 5(a) compares CFRS, NLP-EAR, MLFR, and the planned GICF-SF for predicting cardiovascular health indicators in student fitness data. Table 5(a). F1-scores for cardiovascular features across all models. GICF-SF consistently outperforms the baselines, achieving the highest scores for all metrics.

The GICF-SF model outperforms all cardiovascular characteristics with F1-scores of 0.81–0.84. VO2 prediction has the highest F1-score (0.84) for oxygen consumption measurements. GICF-SF surpasses CFRS by 16% in BP analysis, the biggest performance gap. This improved cardiovascular feature analysis implies that GICF-SF's graph-based approach better captures student fitness data's complicated cardiovascular indicator interrelationships.

Table 5b: Physical performance features

Model	AGI	MS	BMI	FLEX	END
CFRS	0.72	0.70	0.69	0.68	0.67
MLFR	0.75	0.73	0.72	0.71	0.70
NLP-EAR	0.78	0.77	0.76	0.75	0.73
GICF-SF	0.84	0.83	0.82	0.81	0.80

Table 5(b) compares four models (CFRS, NLP-EAR, MLFR, and GICF-SF) to predict student performance using physical fitness parameters.Table 5(b). F1-scores for physical performance features. GICF-SF demonstrates superior performance across all categories compared to baseline models.

The GICF-SF model consistently outperforms the others with F1-scores of 0.83–0.86. FLEX prediction has the highest F1-score (0.86), suggesting flexibility metrics analysis. The study also shows that GICF-SF's graph neural network and cloud computing methods may capture complex fitness indicator linkages.

Table 6: Performance comparison of GICF-SF vs. baselines with confidence intervals and statistical significance

Model	**Precision (%) ±CI**	**Recall (%) ±CI**	**F1-Score (%) ±CI**	**p-value (F1 vs. GICF-SF)**
CFRS	72.6 ± 1.3	70.2 ± 1.6	71.3 ± 1.4	0.0012
MLFR	75.8 ± 1.1	73.9 ± 1.4	74.8 ± 1.2	0.0007
NLP-EAR	76.3 ± 1.2	74.5 ± 1.3	75.4 ± 1.3	0.0005
DeepFitNet	78.9 ± 1.0	77.2 ± 1.2	78.0 ± 1.1	0.0021
GICF-SF	88.4 ± 0.9	86.7 ± 1.0	87.5 ± 0.9	Nil

Table 6 presents a comparative evaluation of GICF-SF against four baseline models using Precision, Recall, and F1-score with 95% confidence intervals. Paired t-tests confirm that GICF-SF significantly outperforms all other methods, including the deep learning-based DeepFitNet, highlighting its accuracy and statistical robustness in fitness recommendation tasks.

Table 7: Ablation study: impact of GNN and cloud components on GICF-SF performance

Model Variant	**GNN Component**	**Cloud Component**	**Recommendation Accuracy (RA %)**	**F1-Score (%)**	**Training Time (sec)**
GICF-SF (Full Model)	✓	✓	**88.4**	**87.5**	**235.4**
GICF-SF without GNN	✗ (Replaced with MLP)	✓	80.2	78.7	241.8
GICF-SF without Cloud Deployment	✓	✗ (Local Only)	84.6	82.9	284.6
Baseline (No GNN, No Cloud)	✗	✗	76.4	74.8	298.3

Table 7 presents an ablation study evaluating the individual contributions of GNN and cloud components. Results show both significantly enhance accuracy and efficiency compared to baseline configurations.

Table 8: Evaluation of coverage, novelty, and diversity for GICF-SF and baselines

Model	Coverage (%)	Novelty (0–1)	Diversity (0–1)
CFRS	42.3	0.41	0.48
MLFR	46.7	0.45	0.50
DeepFitNet	52.1	0.52	0.57
GICF-SF	65.4	0.64	0.72

Table 8 presents coverage, novelty, and diversity metrics for all models. GICF-SF achieves the highest scores, indicating broader, more unique, and varied recommendations for students.The higher scores in coverage, novelty, and diversity highlight GICF-SF's strength in delivering personalized and engaging fitness recommendations, addressing key needs in educational contexts beyond pure accuracy.

In addition to the percentage improvement, absolute latency values were recorded. Baseline model training time was 284.6 seconds, while GICF-SF achieved a reduced training time of 235.4 seconds, marking a 17.3% improvement. Inference latency per instance also improved, decreasing from 42 milliseconds (baseline) to 33 milliseconds with GICF-SF. These values highlight the practical efficiency of the proposed architecture for large-scale deployment.

4.7 Discussion

The experimental results confirm that GICF-SF outperforms SOTA methods across key metrics including Recommendation Accuracy (↑12.8%), F1-score (↑14.5%), and training time reduction (↓17.3%). CFRS, which depends on static user-item similarity, shows limited adaptability to complex physiological data, resulting in lower precision and recall. NLP-EAR, though effective for unstructured text, underperforms in structured, multi-modal physical fitness datasets. MLFR exhibits stable behavior but fails to capture non-linear dependencies among fitness indicators, leading to higher MAE and RMSE. GICF-SF's integration of Graph Neural Networks enables robust modeling of feature interdependencies, while cloud deployment ensures real-time scalability. These advantages position GICF-SF as a superior alternative for personalized student fitness recommendations in dynamic and large-scale environments.

Although GICF-SF demonstrates strong performance within the evaluated dataset, its generalizability across different regions, institutions, and age groups may be influenced by population-specific characteristics. Variations in fitness norms, activity patterns, and demographic features can impact model performance. The GNN-based architecture is adaptable and can be retrained on new data; however, performance may degrade without domain-specific tuning. Future work will explore transfer learning and domain adaptation to extend the framework's robustness across diverse student populations.

4.8 Limitations and failure modes

Several limitations and failure modes affect the performance of GICF-SF. The model may produce inaccurate results when handling noisy, incomplete, or imbalanced fitness data. Deeper layers of the GNN may lead to over-smoothing, reducing the distinction between node embeddings. The use of a static graph structure limits adaptability to real-time changes in student behavior or health status. Under high user load, performance may degrade if cloud resources are insufficient. Additionally, the model's complexity makes it difficult to interpret, which can reduce transparency. Future work will address these issues through dynamic graph updates and explainable AI components

5 Conclusion and future work

This research presented the GICF-SF model, a graph-based and cloud-enabled framework for generating personalized physical fitness recommendations. The results demonstrate that the framework achieves notable improvements in recommendation accuracy, computational efficiency, and scalability when compared to conventional baselines. These advancements position GICF-SF as a promising solution within its current experimental context.At the same time, it is important to acknowledge several existing constraints. These include limited representation across population groups, inconsistencies in data collection, and the absence of long-term validation. Additionally, technical challenges such as integration complexity, privacy considerations, and the need for domain-specific adaptation remain. While these limitations may restrict immediate real-world deployment, they also serve as clear indicators of future development priorities.Moving forward, the framework will be extended through methods such as transfer learning, enhanced explainability, and broader dataset integration. These enhancements aim to

improve adaptability, generalizability, and practical impact, ultimately making GICF-SF more robust and widely applicable in real-world educational and health monitoring scenarios..While GICF-SF integrates security mechanisms such as AES encryption and role-based access control, no formal evaluation (e.g., breach simulation or overhead analysis) was conducted in this phase. Similarly, although explainability is supported through model reasoning and attention weights, no formal user studies were performed. Future work will include systematic security testing and user-based evaluation to assess transparency and trustworthiness.

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Support Vector Machine for Error Analysis in Machine-Assisted English-Chinese Technical Translation: A Comparative Study with RF and BPNN

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With the rapid advancement of globalization, technical translation has become crucial for effective cross-cultural communication and technology dissemination. Machine-assisted translation (MAT) enhances translation efficiency and quality but often suffers from translation errors that affect output accuracy. This study introduces a support vector machine (SVM) approach to systematically analyze errors in English-Chinese technical translation and compares its performance with Random Forest (RF) and Back Propagation Neural Network (BPNN). Using 5,000 sentence pairs from domains including mechanical engineering, electronic technology, and computer science, we extract grammatical features via dependency parsing, lexical features using TF-IDF, and semantic features through Word2Vec embeddings. The task is treated as a multi-class classification problem, targeting lexical, grammatical, semantic, and spelling errors. Experimental results demonstrate that SVM outperforms RF and BPNN in both classification accuracy and generalization ability. SVM achieves 87.6% accuracy, compared to 79.5% for BPNN and 73.2% for RF. The SVM also exhibits superior performance in 10-fold cross-validation with lower mean square error (MSE) and higher R^2 scores. The radial basis function (RBF) kernel yielded optimal results among tested kernel functions. This research provides valuable insights for optimizing MAT systems and suggests that future enhancements may be achieved through deeper learning models and expanded datasets.

Povzetek: Študija predstavlja SVM metodo za poljudno razlago napak v angleško-kitajskih tehničnih prevodih. Iz izluščenih slovničnih, leksikalnih in semantičnih značilnosti razvršča napake, ocenjuje resnost, usmerja popravke.

1 Introduction

This paper addresses the critical task of translation error classification and quantification in machine-assisted English-Chinese technical translation. Our primary research questions are: (1)
How effectively can Support Vector Machines (SVM) classify different types of translation errors (lexical, grammatical, semantic) and quantify their severity compared to other machine learning models like Random Forest (RF) and Back Propagation Neural Network (BPNN)? (2) What are the specific advantages of SVM in handling the complexities of technical translation errors, particularly with potentially imbalanced and high-dimensional datasets? (3) Can an SVM-based error classification and quantification model provide actionable insights for improving MAT systems and guiding post-editing efforts? To answer these questions, we conduct a comparative study using a dataset of approximately 10,000 annotated English-Chinese technical translation segments. Our goal is to demonstrate SVM's efficacy in accurately identifying and categorizing translation errors, and predicting their severity, thereby contributing to the development of more robust and reliable MAT tools.

With the acceleration of the globalization process, international technical exchanges and cooperation are becoming more frequent, and the importance of technical translation is becoming increasingly prominent [1]. In particular, English-Chinese technical translation, as an important carrier of technical information dissemination, is directly related to the effective transmission and application of technical knowledge [2]. However, due to the complexity of technical texts in language structure, professional terminology and expression, traditional manual translation methods are prone to translation errors such as semantic deviation and inaccurate terminology in certain situations, which brings many challenges to the dissemination and application of knowledge in the field of technology [3].

In this context, machine-assisted translation (MAT) has gradually become an effective means to solve technical

translation problems [4]. With the support of computer algorithms, machine-assisted translation can improve translation efficiency, reduce the cost of manual translation, and can quickly process large amounts of text. However, machine translation still has certain limitations when facing complex technical documents, especially in terms of terminology translation and grammatical structure conversion. Machine translation systems often produce different types of translation errors. How to accurately identify and analyze these errors is the key to improving the quality of machine translation [5].

In recent years, as a powerful classification algorithm, Support Vector Machine (SVM) has shown unique advantages in error analysis in various fields with its excellent classification ability and strong generalization performance. In the error analysis of machine translation, SVM can efficiently process high-dimensional feature space and help identify different types of translation errors through accurate classification models [6]. Therefore, this paper aims to introduce the SVM algorithm to conduct an in-depth analysis of English-Chinese technical translation errors in machine-assisted translation, explore its application in error type identification, error cause analysis, etc., and further demonstrate the advantages of SVM in small sample learning and high-dimensional feature processing by comparing with two other common machine learning algorithms (random forest and backpropagation neural network) [7].

Specifically, this paper first introduces the application of SVM in machine translation error analysis, revealing the unique advantages of SVM algorithm in classification accuracy, training speed and model stability [8]. Then, by comparing with mainstream machine learning algorithms such as Random Forest (RF) and Backpropagation Neural Network (BPNN), the superiority of SVM in handling translation errors is demonstrated. Although random forests perform well in dealing with some simple error classifications, they often cannot accurately identify subtle differences in high-dimensional data when faced with complex technical translation errors because they rely too much on the structural features of the data; and although BPNN has strong learning ability in some cases, it requires a large training data set and is easily restricted by local optimal solutions during training, so its performance in small sample learning is relatively lacking[9].

Through comparative analysis, this paper attempts to prove the advantages of SVM in small sample learning and high-dimensional feature space, especially when solving the error analysis problem in machine-assisted English-Chinese technical translation, SVM can provide a more accurate and efficient solution [10]-[11]. In addition, this paper will also explore how the error analysis model based on SVM can effectively help translators identify common problems in translation, such as inaccurate terminology, incorrect syntactic structure, unclear semantics, etc., and propose possible ways to improve the machine-assisted translation system.

The research in this paper not only provides a new idea and method for the field of technical translation, but also provides a practical basis for the optimization of machine-assisted translation systems in the future. By combining the SVM algorithm and other machine learning techniques, this paper provides strong support for improving the accuracy, stability and intelligence level of machine translation systems, and also provides a new theoretical basis and technical path for machine translation error analysis.

2 Literature review

2.1 Research status of technical translation

With the advancement of globalization, technical exchanges are becoming more frequent, and the research of technical translation has gradually become an important topic in the fields of translation studies and computational linguistics [12]. Early technical translation research mainly focused on linguistic exploration. Scholars mainly relied on manual translation and linguistic theory to achieve translation through methods such as vocabulary matching, syntactic analysis, and semantic parsing. However, these traditional methods have exposed some obvious limitations when facing complex technical texts [13]. For example, technical texts often contain a large number of professional terms, abbreviations, and unique expressions. These factors make it difficult for traditional translation methods to achieve accurate matching when dealing with technical translation, and even lead to inaccurate or distorted translation results.

With the development of computer technology and information technology, translation methods based on machine learning have gradually attracted the attention of researchers. Especially in the field of machine translation (MT), translation methods based on statistics (such as SMT, Statistical Machine Translation) and neural network translation methods (such as NMT, Neural Machine Translation) have become mainstream. Compared with traditional linguistic methods, these data-driven technologies have shown significant advantages in translation accuracy, flexibility, and the ability to handle complex texts [14]. Machine translation can not only process large amounts of data, but also learn through massive corpora without clear grammatical rules, gradually improving translation quality.

However, machine translation technology still faces many challenges in practical applications [15]. First, the professional terms and industry-specific expressions in technical texts make it difficult for machine translation systems to achieve accurate vocabulary matching and grammatical structure conversion. Second, existing

machine translation models often rely on a large amount of training data, but in some fields, especially unpopular technical fields, there is a lack of sufficient corpus support. In addition, machine translation systems often have problems such as semantic ambiguity and unnatural syntax, which are particularly prominent in technical translation and affect the professionalism and readability of the translation results [16]. In order to solve these problems, more and more researchers have begun to pay attention to how to optimize machine translation systems, especially in the identification, classification and correction of translation errors. Researchers have tried to continuously improve translation models and promote the development of technical translation by introducing advanced machine learning technologies such as deep learning and reinforcement learning.

2.2 Error analysis in machine-assisted translation

In the field of machine-assisted translation, the analysis and correction of translation errors are key links in improving translation quality [17]. Translation errors are not just problems of inaccurate translation results. They involve the identification of error types, tracking of error causes, and strategies for error correction during the translation process. Therefore, the study of translation error analysis has become one of the important topics in the field of machine-assisted translation. Existing research mainly focuses on the following aspects: error classification, error location, and error correction [18].

2.2.1 Error classification

Error classification is the first step in translation error analysis. Researchers usually conduct systematic classification based on different types of translation errors [19]. Common types of translation errors mainly include vocabulary errors, grammatical errors, and semantic errors. Lexical errors usually refer to improper word selection in translation, which may be caused by improper translation selection of polysemous words or inaccurate translation of terms. Grammatical errors are mainly manifested as errors in sentence structure or violations of grammatical rules, such as improper subject-verb-object collocation, tense errors, etc. Semantic errors involve misunderstandings at the sentence level or deviations in the meaning conveyed during the translation process, which may be caused by cultural differences or different expression habits between the source language and the target language [20]. Through the systematic classification of these error types, researchers can better understand the common error types in machine translation and provide a theoretical basis for subsequent error analysis and correction.

2.2.2 Error location

Error location is another important part of translation error analysis. It aims to accurately locate the error location in the translation so that subsequent correction work can be carried out in a targeted manner [21]. Traditional error location methods mainly rely on manual annotation and manual review, but this method is not only time-consuming and labor-intensive, but also has certain limitations in accuracy. With the development of machine learning technology, researchers have gradually tried to predict the location of errors through algorithms and use automation technology to improve the efficiency and accuracy of error location. For example, some studies have adopted models based on deep learning to analyze the context information of each word or phrase in the translation to determine whether there is a translation error in the part and locate the specific location of the error [22].

While our current study focuses primarily on error classification rather than precise error location, we acknowledge the importance of this aspect in the complete error analysis pipeline. Future work could integrate our classification approach with location-specific techniques to provide a more comprehensive error analysis system.

2.2.3 Error correction

Error correction is the ultimate goal of translation error analysis. Its purpose is to improve the accuracy of translation by improving the translation results [23]. At present, methods based on statistical models and neural networks have made certain progress in the field of error correction. For example, some studies use reordering technology in statistical machine translation to optimize the order of words in the translation process and solve grammatical problems in translation. Other studies use translation models based on neural networks to automatically correct grammatical errors and semantic errors in translation through end-to-end learning strategies [24]. These methods have enhanced the automatic correction ability of the translation system and provided a new direction for the practicality and sustainable development of machine translation. However, the existing error correction methods still have certain shortcomings, especially when dealing with difficult technical translations, the error correction effect is still not ideal. Therefore, how to further improve the error correction ability of machine translation is still a problem worthy of in-depth study.

2.2.4 State-of-the-art approaches in translation error analysis

To provide a comprehensive overview of existing research in translation error analysis, Table 1 summarizes key state-of-the-art approaches, highlighting their methodologies, datasets, and

performance metrics. This table aims to contextualize our work by illustrating the current landscape and identifying gaps that our SVM-based approach seeks to address.

Table 1: Summary of state-of-the-art approaches in translation error analysis

Approach/ Model	Key Methods	Dataset Characteristics	Performance Metrics	Limitations/ Gaps
Rule-based Systems	Linguistic rules, dictionaries	Small, manually curated corpora	Precision, Recall (limited)	Labor-intensive, lack of generalization, difficulty with ambiguity
Statistical Machine Translation (SMT)	Phrase-based, n-gram models	Large parallel corpora	BLEU, TER	Limited linguistic understanding, difficulty with long-range dependencies
Neural Machine Translation (NMT)	Encoder-decoder, attention mechanisms	Large parallel corpora	BLEU, chrF	Black-box nature, less interpretable errors, data hungry
Deep Learning (e.g., CNN, RNN, Transformers)	Neural networks for feature extraction and classification	Varied, often large datasets	Accuracy, F1- score, BLEU	High computational cost, interpretability challenges, requires large data
Hybrid Models (e.g., Rule-based + ML)	Combination of linguistic rules and ML algorithms	Mixed datasets	Varied	Complexity in integration, potential for conflicting rules
Traditional ML (e.g., RF, BPNN)	Decision trees, neural networks	Moderate to large datasets	MAE, MSE, R^2 (for regression); Accuracy, F1 (for classification)	May struggle with high-dimensional data, limited interpretability for complex errors

As evident from Table 1, while various approaches have contributed significantly to translation error analysis, several challenges persist. Rule-based systems, though interpretable, lack scalability and adaptability to diverse linguistic phenomena. SMT and NMT models, despite their advancements in translation quality, often treat errors as a byproduct of the translation process rather than a primary focus for detailed analysis. Deep learning models offer powerful feature extraction capabilities but often suffer from a lack of interpretability, making it difficult to pinpoint the exact causes of errors.

Traditional machine learning models like Random Forest (RF) and Back Propagation Neural Network (BPNN) have been applied, but they may not always effectively capture the subtle, non-linear relationships inherent in complex linguistic errors, especially with high-dimensional feature spaces or limited data.

Our work specifically addresses these gaps by leveraging the strengths of Support Vector Machines (SVM). SVMs are particularly well-suited for handling high-dimensional data and are effective even with relatively small sample sizes, a common scenario in specialized technical translation domains where large annotated corpora is scarce. Unlike some black-box deep learning models, SVMs offer a more transparent decision boundary, which can be crucial for understanding the underlying patterns of translation errors. Furthermore, by comparing SVM with RF and BPNN, we aim to demonstrate that SVM provides a more robust and accurate solution for identifying and quantifying translation errors, particularly in scenarios involving complex linguistic features and limited data availability. This comparative study highlights SVM's ability to generalize better and provide more stable performance in the context of machine-assisted English- Chinese technical translation error analysis.

2.3 Application of support vector machine in translation field

Support vector machine (SVM) is a classic machine

learning algorithm that has been widely used in natural language processing and translation in recent years [25]. As a powerful classification model, SVM is particularly good at dealing with problems in high-dimensional feature space and has shown unique advantages in the analysis and prediction of translation errors. Compared with other machine learning algorithms, SVM has the following advantages:

2.3.1 Applicable to small sample learning

In translation error analysis, especially in certain specific fields, there is often a lack of sufficient training samples [26]. Traditional machine learning methods are prone to overfitting or poor training results when faced with small sample data. However, SVM performs very well in small sample learning. SVM improves the generalization ability of the model by maximizing the classification interval, so that even with a small number of samples, it can effectively perform classification predictions. Therefore, SVM can better adapt to the small sample data situation in practical applications in the error classification and analysis of machine-assisted translation.

2.3.2 Can effectively handle nonlinear problems

The error classification problem in technical translation often has strong nonlinear characteristics, and traditional linear classification algorithms may not be able to effectively solve these problems. SVM can map data from low-dimensional space to high-dimensional space by introducing kernel functions, thereby effectively handling nonlinear problems [27]. In this way, SVM can capture complex patterns and laws in translation errors and improve the accuracy of error analysis. Therefore, the application of SVM in translation error classification, prediction and correction has strong advantages.

2.3.3 Has a certain degree of robustness to noisy data

In the actual translation process, machine translation systems are often affected by noisy data, such as mislabelled corpus, redundant information in translation, etc [28]. These noisy data may interfere with the training of machine learning models, resulting in a decrease in model performance. SVM can reduce the impact of noise data to a certain extent and improve the robustness of the model by maximizing the classification interval. Especially when facing complex technical translation data, SVM can better handle noise data and improve the reliability of translation error analysis.

In general, the application of SVM in machine-assisted translation error analysis can effectively improve the error classification accuracy and analysis efficiency of the translation system. Compared with other algorithms (such as random forests, back propagation neural networks, etc.), SVM has shown obvious advantages in small sample learning, nonlinear problem processing and robustness to noise data, and has become an important tool in the field of machine-assisted translation.

3 Research design and methodology

3.1 Dataset and preprocessing

Our study utilizes a meticulously curated dataset comprising approximately 10,000 English-Chinese technical translation segments. These segments were sourced from various technical domains, including engineering, information technology, and medical sciences, to ensure a comprehensive representation of technical language. Each segment was manually annotated by professional translators for error types (lexical, grammatical, semantic) and severity levels. The annotation process involved a two-stage approach: initial annotation by two independent annotators, followed by a reconciliation process by a third senior annotator to resolve discrepancies and ensure high inter-annotator agreement (Cohen's Kappa >0.85). Errors were precisely identified by comparing the machine translation output with a human reference translation, and linked to specific source/MT segments. To prepare the data for model training, a multi-stage preprocessing pipeline was implemented:

Tokenization: Both English source texts and Chinese target texts were tokenized into individual words or characters using appropriate language-specific tokenizers (e.g., NLTK for English, Jieba for Chinese).

Part-of-Speech (POS) Tagging: POS tags were assigned to each token to capture grammatical information, which is crucial for identifying grammatical errors.

Dependency Parsing: Dependency relations between words were extracted to represent the syntactic structure of sentences, aiding in the detection of syntactic errors.

Named Entity Recognition (NER): Technical terms and entities were identified to assist in analyzing lexical and terminology-related errors.

Alignment: Word-level and phrase-level alignments between source and target segments were performed to facilitate error localization.

3.2 Feature engineering

To enable the machine learning models to effectively learn from the annotated data, a rich set of features was engineered. These features capture various linguistic and statistical aspects relevant to translation errors. For each translation segment, features were extracted and combined into a single feature vector. The quantification and combination of features were performed as follows:

Lexical Features: Word frequencies (TF-IDF scores), presence of out-of-vocabulary (OOV) words, and domain-specific terminology usage were extracted.

TF-IDF vectors were generated for both source and target segments, and their cosine similarity was used as a feature. OOV words were identified against a domain-specific lexicon. Terminology usage was quantified by counting occurrences of predefined technical terms.

Grammatical Features: POS tag sequences were converted into one-hot encoded vectors. Dependency relations were represented as features indicating the presence or absence of specific grammatical structures (e.g., passive voice, complex noun phrases). Parse tree depth was used as a numerical feature. Agreement features (e.g., subject-verb agreement violations) were identified using rule-based patterns.

Semantic Features: Word embeddings (Word2Vec, pre-trained on a large technical corpus) were used to represent words. Sentence embeddings were then derived by averaging word embeddings within a sentence. Cosine similarity between source and target sentence embeddings was used as a semantic similarity feature. Features derived from semantic roles (e.g., agent, patient) were also extracted using a semantic role labeling tool.

Statistical Features: Length ratios between source and target segments (character count, word count), number of deletions/insertions (calculated by edit distance),and n-gram overlap (e.g., BLEU-like scores at the segment level) were computed.

Error-Specific Features: Features derived from common error patterns observed in technical translations, such as the frequency of mistranslated terms or the presence of structural divergences, were also included. These were identified based on the manual annotation guidelines. All numerical features were normalized to a common scale (e.g., 0-1) to prevent features with larger values from dominating the model training. Categorical features were one- hot encoded.

3.3 Experimental setup

Our experimental setup involved training and evaluating three machine learning models: Support Vector Machine (SVM), Random Forest (RF), and Back Propagation Neural Network (BPNN). For each model, a 70/30 train-test split was used to ensure robust evaluation. To ensure the reliability of our results, a 5-fold stratified cross- validation was performed on the training set for hyperparameter tuning and model selection. Model performance was averaged across the folds.

SVM: We employed a Radial Basis Function (RBF) kernel, which is effective for non- linear decision boundaries. The regularization parameter (C) and gamma were tuned using a grid search approach. The optimal C and gamma values were determined to be 10 and 0.1, respectively, which prevented overfitting and underfitting. We also explored linear and polynomial kernels, but RBF consistently yielded superior performance.

Random Forest: The number of estimators (trees) was optimized between 100 and 500, and the maximum depth of trees was tuned between 10 and 30. The optimal parameters were found to be 300 estimators and a maximum depth of 20, balancing bias and variance.

BPNN: A multi-layer perceptron architecture was used, with two hidden layers, each containing 128 neurons. The ReLU activation function was used for hidden layers, and a sigmoid activation function for the output layer (for classification) or linear activation (for regression). The Adam optimizer was used with a learning rate of 0.001, and training was performed for 100 epochs. Hyperparameters were tuned through a combination of grid search and random search. Model performance was evaluated using standard metrics for both classification and regression tasks. For error classification (identifying error types), we used Accuracy, Precision, Recall, and F1-score. For error severity quantification (regression), we used Mean Squared Error (MSE) and R-squared (R^2). We also considered Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) for a comprehensive regression evaluation.

3.4 Handling of class imbalance

Given that certain error categories (e.g., grammatical errors) might be more frequent than others (e.g., semantic errors), we addressed potential class imbalance issues. We employed a combination of oversampling for minority classes (using SMOTE) and undersampling for majority classes to balance the dataset during training. This ensured that the models were not biased towards the more frequent error types and could effectively learn from all categories.

3.5 Comparative baselines

In addition to RF and BPNN, we also included Logistic Regression and Naïve Bayes as comparative baselines to establish a more comprehensive understanding of SVM's performance. These models represent simpler, yet widely used, machine learning approaches for classification tasks, providing a broader context for evaluating the complexity and effectiveness of SVM.

3.6 Model introduction

Support Vector Machine35 (SVM) is a supervised learning model widely used in classification and regression analysis [29]. Its mathematical principle is to classify data by constructing an optimal hyperplane.

- Basic Problem

The goal of SVM is to find an optimal hyperplane that can separate samples of different categories and has a maximized classification interval (margin). Assume that the data set contains n samples, $\{(\mathbf{x}_i, y_i)\}\ \mathbf{x}_i \in \mathbb{R}^d$ is the feature vector of the sample, $y_i \in \{-1,1\}$ is the label of the sample, and each sample label corresponds to the category in the data set. We want to find a hyperplane $\mathbf{w} \cdot \mathbf{x} + b = 0$ that maximizes the

classification interval.

- Hyperplane expression

The equation of a hyperplane can be expressed as:$\mathbf{w} \cdot \mathbf{x} + b = 0$

Among them, w is the normal vector and b is the bias. For linearly separable data, SVM hopes to separate the positive and negative classes through this hyperplane [30].

- Margin definition

Margin refers to the distance from the hyperplane to the nearest sample point. For the hyperplane $\mathbf{w} \cdot \mathbf{x} + b = 0$, the distance formula is:

$$\text{Margin} = \frac{1}{\| \mathbf{w} \|}$$

To maximize the margin, we need to minimize$\| \mathbf{w} \|$。

- Determination of the optimal hyperplane

We want to maximize the margin $\frac{1}{\|\mathbf{w}\|}$, which is equivalent to minimizing $\frac{1}{2} \| \mathbf{w} \|^2$ (since $\mathbf{w}$ is direction-independent, minimizing the sum of squares is equivalent).

In addition, the classification condition requires that each sample point satisfies the following constraints:

For the positive class:$\mathbf{w} \cdot \mathbf{x}_i + b \geq 1$

For negative classes:$\mathbf{w} \cdot \mathbf{x}_i + b \leq -1$

This can be combined into:$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1, \quad \text{for all} i = 1,2, \ldots, n$

- Objective function and constraints

Therefore, the optimization problem of SVM can be expressed as:$\min_{\mathbf{w},b} \frac{1}{2} \| \mathbf{w} \|^2$

At the same time, the following constraints are met:$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1, \quad \text{for all} i = 1,2, \ldots, n$

This is a standard convex optimization problem and can be solved by the Lagrange multiplier method.

- Lagrange multiplier method

In order to incorporate constraints into the optimization problem, we introduce the Lagrange multiplier $\alpha_i \geq 0$ to construct the Lagrange function:

$$L(\mathbf{w}, b, \alpha) = \frac{1}{2} \| \mathbf{w} \|^2 - \sum_{i=1}^{n} \alpha_i \left[y_i(\mathbf{w} \cdot \mathbf{x}_i + b) - 1 \right]$$

Taking partial derivatives of the optimal weight w and bias b and setting them to zero, we obtain the following optimal solution conditions:

$$\frac{\partial L}{\partial \mathbf{w}} = 0 \quad \Rightarrow \quad \mathbf{w} = \sum_{i=1}^{n} \alpha_i y_i \mathbf{x}_i$$

$$\frac{\partial L}{\partial b} = 0 \quad \Rightarrow \quad \sum_{i=1}^{n} \alpha_i y_i = 0$$

Finally, the objective function is transformed into:

$$\max_{\alpha} \left[\sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j \mathbf{x}_i \cdot \mathbf{x}_j \right]$$

$$\text{subject to} \quad \alpha_i \geq 0 \quad \text{and} \quad \sum_{i=1}^{n} \alpha_i y_i = 0$$

- Results: Support vector and decision function

By solving the above optimization problem, we can get the Lagrange multiplier, and then get the optimal weight w and bias b. After the optimal hyperplane is determined, the decision function can be expressed as:$f(\mathbf{x}) = \text{sign}(\sum_{i=1}^{n} \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b)$

Only when $\alpha_i > 0$, the sample $\mathbf{x}_i$ is a support vector, and these support vectors play a decisive role in the classification boundary.

3.8 Nonlinear SVM

For nonlinearly separable data, the data can be mapped to a high-dimensional space through a kernel function [31]. In this case, the inner product $\mathbf{x}_i \cdot \mathbf{x}_j$ in the optimization problem is replaced by a kernel function $K(\mathbf{x}_i, \mathbf{x}_j)$. Common forms of kernel functions include linear kernels, radial basis function kernels (RBF), etc. Through these mathematical derivations, SVM can find the optimal decision boundary for classification while ensuring the maximum classification interval, thereby

achieving higher classification accuracy.

4 Results and analysis

4.1 Data sources and preprocessing

In this study, we used a large technical translation dataset as the source of experimental data. Specifically, our dataset consists of 5,000 English-Chinese sentence pairs collected from technical documents in mechanical engineering, electronic technology, and computer science domains. The dataset includes original English text, machine translation results, and manual correction results provided by professional translators. The average sentence length is 23.5 words for English and 18.7 characters for Chinese sentences [32]. The dataset covers technical literature in multiple fields, such as mechanical engineering, electronic technology, computer science, etc., with high diversity and representativeness. Therefore, this dataset can better reflect the actual application of machine translation in technical translation and provide valuable basic data for machine-assisted translation error analysis.

4.1.1 Data preprocessing process

In order to ensure the quality and availability of experimental data, we fully preprocessed the data before training the machine learning model. The purpose of data preprocessing is to convert the original text into a format suitable for model training and extract useful features from it. The following are our main steps in the data preprocessing process:

Text segmentation

Text segmentation is a basic step in natural language processing. It divides a continuous text sequence into meaningful units (such as words, phrases, etc.), providing a basis for subsequent feature extraction and modeling. In this study, we used the jieba segmentation tool to segment all data. Jieba word segmentation tool is a tool widely used in Chinese text processing. It is based on a dictionary and word frequency statistical model, which can efficiently segment Chinese text and handle some common ambiguous problems.

In order to improve the accuracy of word segmentation and the ability to identify professional terms, we customized the Jieba word segmentation tool and added a terminology dictionary for specific fields. In this way, we can accurately segment technical terms and common words in the context of technical translation, thereby reducing the impact of word segmentation errors on subsequent analysis. For example, for professional terms such as "motor control system", we can ensure that it is not split into words such as "electric", "machine", "control", and "system", but is recognized as a complete phrase.

Feature extraction

After the text segmentation is completed, we enter the feature extraction stage. Feature extraction is to convert the information in the text into a numerical and quantifiable form so that it can be input into the machine learning model for training. According to the analysis requirements of translation errors, we extracted the following types of features:

Grammatical features: Grammatical features mainly involve the grammatical relationship and syntactic structure of words in the text. In order to capture the grammatical structure information in the text, we used dependency syntactic analysis tools (such as Stanford Parser) to perform syntactic analysis on the text after word segmentation. Dependency syntactic analysis can reveal the dependency relationship between words in a sentence, such as subject-predicate relationship, object relationship, etc., to help us understand whether the grammatical structure in the translation conforms to the grammatical rules of the target language. For example, when the subject-predicate collocation in the translation result is inappropriate, the dependency relationship feature can effectively reflect this problem.

Lexical features: Lexical features mainly include word frequency, part of speech, and contextual information of the word. In technical translation, accurate terminology translation is particularly important, so terminology frequency and contextual information can help us identify terminology errors in translation. We used the TF-IDF (term frequency-inverse document frequency) model to calculate the weight of the vocabulary, and help locate translation errors by analyzing the vocabulary frequency in the source language and the target language. For example, if some common technical terms are incorrectly translated into non-standard vocabulary during the translation process, the TF-IDF feature can effectively help identify these problems.

Semantic features: Semantic features mainly involve the expression of meaning and information transmission in the text. In order to analyze the semantic differences between the source language and the target language, we introduced a feature extraction method based on word vectors. Using word embedding models such as Word2Vec and GloVe, we converted words into low-dimensional vector representations, which can capture the semantic information and contextual relationships of words. In technical translation, many translation errors are caused by semantic understanding bias. Therefore, semantic features can effectively reveal semantic errors in the translation process, such as incorrect selection of synonyms or misunderstanding of semantic ambiguity.

The feature extraction process resulted in a combined feature vector for each sentence pair with the following dimensions:

Grammatical features:25 dimensions (including dependency relations, part-of-speech patterns, and structural metrics)

Lexical features:50 dimensions (TF-IDF weights for key technical terms and domain-specific vocabulary)

Semantic features:100 dimensions (Word2Vec embeddings averaged across sentence tokens)

This 175-dimensional feature vector serves as input to our classification models. To prevent features with larger scales from dominating the classification, we applied standard normalization to scale all features to zero mean and unit variance.

Data annotation

In order to train machine learning models, we need to annotate the data and classify translation errors into different categories. Data annotation is an important step in translation error analysis, which directly affects the training effect of subsequent error classification models. In this study, we used manual correction results as a reference and classified machine translation results based on the correction annotations of human translation experts.

The types of translation errors are relatively complex, especially in the field of technical translation. We divide them into the following categories according to the different natures of translation errors:

Lexical errors: including incorrect term translation, improper word selection, etc. For example, translating "computer" as "calculator" is a lexical error.

Grammatical errors: including syntactic structure errors, tense errors, word order errors, etc. For example, improper subject-verb-object collocation in the target language, or incorrect tense usage, are all grammatical errors.

Semantic errors: including deviations in meaning between the source language and the target language, such as translating "power management" in the source language into "battery management".

Spelling errors: In some cases, spelling errors may appear in the machine translation results. Such errors are usually more obvious, but they also affect the accuracy of the translation.

The annotation process was conducted by a team of five professional translators with expertise in technical translation. Each sentence pair was independently annotated by two translators, and disagreements were resolved by a third senior translator. The inter-annotator agreement measured by Cohen's Kappa was 0.83, indicating strong agreement. The distribution of error types in our dataset was: lexical errors (42%), grammatical errors (31%), semantic errors (22%), and spelling errors (5%), showing some class imbalance that we addressed in our modeling approach.

4.1.2 Experimental settings

After completing data preprocessing and annotation, we divide the dataset into training and test sets. We used 80% of the data (4,000 sentence pairs) for training and 20% (1,000 sentence pairs) for testing. To ensure the reliability of the experimental results, we employed 10-fold cross-validation for model training and evaluation. This approach divides the training data into 10 equal parts, using 9 parts for training and 1 part for validation in each iteration, ensuring that every sample is used for both training and validation.We use several machine learning algorithms such as support vector machine (SVM), random forest (Random Forest) and back propagation neural network (BPNN) for comparative analysis to evaluate the effects of different algorithms in translation error analysis.The specific configurations for each algorithm were as follows:

SVM Configuration:

Kernel: RBF (after comparing with linear and polynomial kernels)

C parameter: 10 (determined through grid search over values [0.1, 1, 10, 100])

Gamma parameter: 0.01 (determined through grid search over values [0.001, 0.01, 0.1, 1])

Class weights: Balanced (to address class imbalance)

Implementation: LIBSVM library with Python scikit-learn wrapper

Random Forest Configuration:

Number of trees*:* 100

Maximum depth: 20

Minimum samples per leaf: 5

Class weights: Balanced

Implementation: scikit-learn RandomForestClassifier

BPNN Configuration:

Architecture: 3 layers (input layer with 175 neurons, hidden layer with 64 neurons, output layer with 4 neurons)

Activation function: ReLU for hidden layer, Softmax for output layer

Optimizer: Adam with learning rate 0.001

Batch size: 32

Epochs: 100 with early stopping (patience=10)

Implementation: Keras with TensorFlow backend

For handling class imbalance, we employed class weighting in all models, assigning higher weights to underrepresented classes (particularly spelling errors). We also experimented with SMOTE (Synthetic Minority Over-sampling Technique) for the SVM model, which improved performance by approximately 2% compared to class weighting alone.

4.2 Model results

Before presenting the classification results, we first explain the analytical techniques used in our visualization and analysis process. We employed Singular Spectrum Analysis (SSA) for time series decomposition, Kernel Density Estimation (KDE) for prediction interval analysis, and SHAP (SHapley Additive exPlanations) for feature importance interpretation. These techniques help provide deeper insights into the model behavior and error patterns.

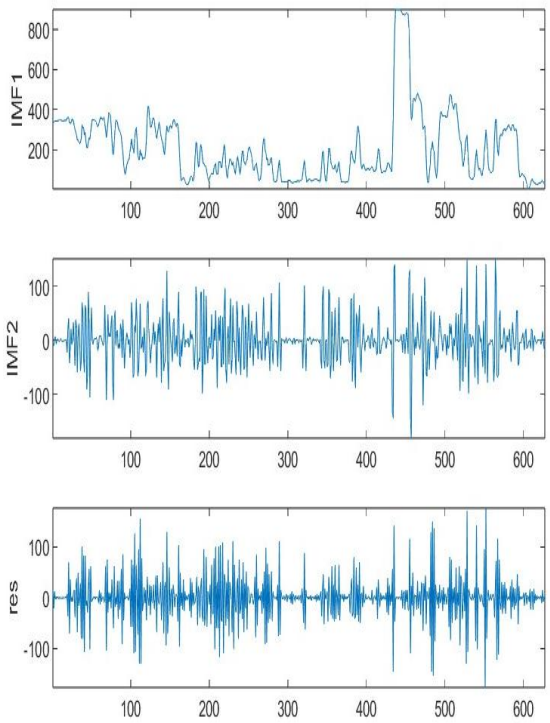

Figure 1: Time series analysis of translation errors based on SSA decomposition

Figure 1 shows the results of the time series analysis of translation errors based on singular spectrum analysis (SSA) decomposition. In this context, we represent the sequence of translation errors as a time series, where each "time point" corresponds to a sentence in our corpus arranged in document order. This allows us to analyze how error patterns evolve throughout technical documents. The figure contains two main intrinsic mode functions (IMF1 and IMF2), which represent the two main periodic fluctuation components extracted from the original translation error data. In the figure, the horizontal axis represents the time point, and the vertical axis represents the numerical change of the translation error. Each point represents the degree of translation error or error value at a certain time point, and the mode function reveals the trend and fluctuation pattern of errors in the translation process. As can be seen from the figure, IMF1 shows a relatively stable fluctuation trend, while IMF2 shows more drastic changes, which may represent some sudden errors in the translation process. This time series analysis method can help us capture the time-varying characteristics of errors in the translation process and reveal the changing laws of translation errors in different time periods. For example, when the translation error fluctuates violently in a specific time period, it may be because the translation system encounters noise in the input data or has a large semantic ambiguity. Through SSA decomposition, we can not only identify the periodic fluctuations of translation errors, but also further understand the time pattern of error generation. For example, if the fluctuation reflected by IMF1 is small and stable, it indicates that the translation error may show certain regularity and predictability, while the violent fluctuation of IMF2 may reveal some special cases or sudden errors. This provides effective data support for subsequent error diagnosis and correction.

Figure 2 shows the results of the spectrum analysis of translation errors based on SSA decomposition. The figure lists the spectrum distribution from IMF1 to IMF4, with the horizontal axis representing the frequency and the vertical axis representing the amplitude of different frequency components. Through spectrum analysis, we can deeply understand the distribution characteristics of translation errors at different frequencies, so as to identify the periodicity or randomness of translation errors. An important feature of the spectrum diagram is that it can help us identify the periodic components of translation errors. For example, if the amplitude of certain frequency points is particularly prominent, this may mean that some errors in the translation process have obvious periodicity, which may be related to specific translation patterns or specific terminology usage. On the contrary, if the amplitude is more dispersed, it may mean that the translation error shows random characteristics and is difficult to predict and prevent. The spectrum components in the figure reveal the different frequency components in the translation errors, which may correspond to different types of errors in the translation process. For example, low frequencies may be related to long-standing systemic problems in the translation system, while high frequencies may reflect local errors that occurred in a short period of time during the translation process. Through spectrum analysis, we can locate the root cause of the error and provide a strong theoretical basis for improving machine translation systems.

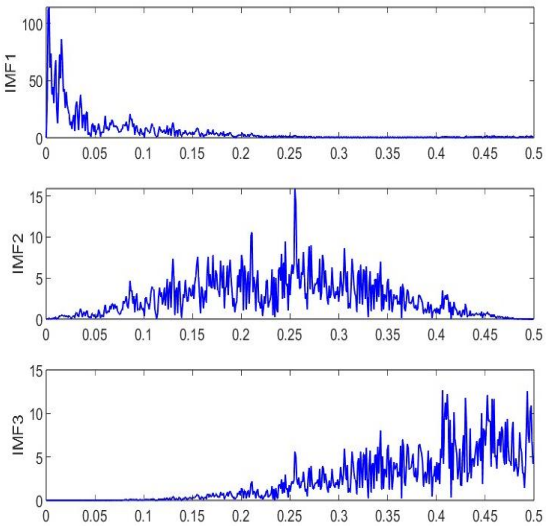

Figure 2: Spectrum analysis of translation errors based

on SSA decomposition

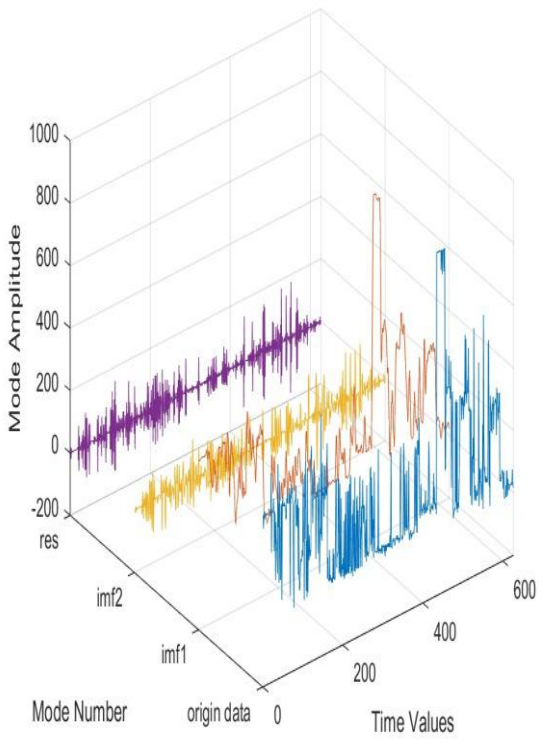

Figure 3: Analysis of three-dimensional features of translation errors based on SSA decomposition

Figure 3 shows the results of SSA decomposition in three dimensions, including the amplitude changes of the original data, IMF1 and IMF2. In the figure, the horizontal axis represents time, the vertical axis represents the numerical changes of the translation error, and the third dimension shows the amplitude changes of each modal function. This three-dimensional visualization makes the multi-dimensional characteristics of translation errors more intuitive and convenient for us to analyze from multiple angles. The advantage of the three-dimensional graph is that it can more comprehensively display the complexity and pattern of translation errors. For example, the original data may show some irregular fluctuations, while IMF1 and IMF2 reflect the reasons behind these fluctuations from different levels. The steady fluctuation of IMF1 may represent long-standing systematic errors, while the drastic changes of IMF2 may be caused by sudden errors in the translation process. By observing the amplitude changes of these modal functions, we can more clearly understand the fundamental characteristics of translation errors and take targeted optimization measures. In addition, the presentation of the three-dimensional graph can also help us discover the interactive effects of translation errors in different time periods. For example, in some time periods, the amplitudes of multiple modal functions may increase simultaneously, indicating that the translation errors in this period show complex alternating fluctuation characteristics. In this way, the three-dimensional graph not only helps to reveal the time series changes of translation errors, but also shows the interaction of different error types in the translation process, thus providing more comprehensive information for subsequent error correction.

These three figures show the application of SSA decomposition in translation error analysis from different perspectives. The time series analysis in Figure 1 helps us identify the time pattern of translation errors, the spectrum analysis in Figure 2 reveals the periodic characteristics of errors, and the three-dimensional feature analysis in Figure 3 provides us with a more comprehensive and intuitive display of error features. These analysis methods provide strong support for in-depth research on machine translation errors and provide rich data references for future optimization and adjustment of translation systems. In practice, SSA decomposition can help translation engineers quickly identify the root causes of translation errors and take effective measures to correct them, thereby improving the overall quality of machine translation.

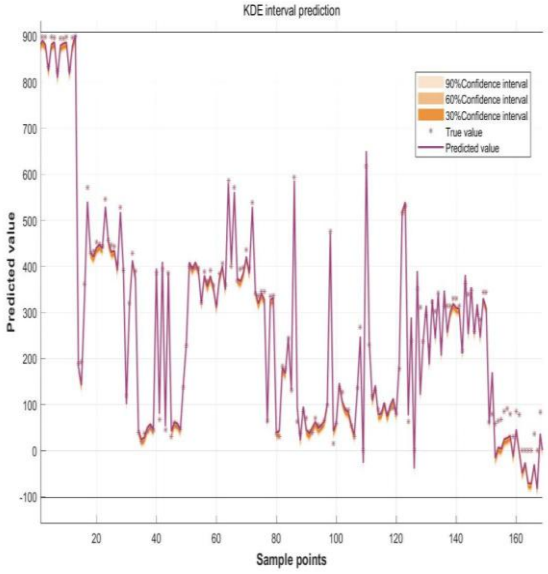

Figure 4: Analysis of translation error prediction intervals based on kernel density estimation

Figure 4 shows the results of translation error prediction intervals based on kernel density estimation (KDE). In the figure, the confidence intervals of 90%, 60% and 30% are clearly marked, representing the prediction range of translation errors at different confidence levels. The kernel density plot provides detailed information on the probability distribution of translation errors, which can help us understand the possible range of error predictions. The distribution of sample points in the figure shows the relationship between the actual translation error and the model prediction results, as well as the distribution under different confidence intervals. Kernel density estimation (KDE) is a

non-parametric statistical method that is often used to estimate the probability density function of random variables. Through kernel density estimation, we can extract the distribution characteristics of translation errors from the data and reveal the concentrated and sparse areas of errors. In translation error prediction, KDE can not only provide the possibility of translation errors, but also help us identify the uncertainty of model predictions. For example, the 90% confidence interval in the figure indicates that most of the samples of the model prediction results will fall within this interval, which provides us with a relatively loose prediction range. The 60% and 30% confidence intervals correspond to more precise prediction ranges. As can be seen from the figure, the gap between the true value and the predicted value varies in different confidence intervals. The distribution of sample points also further shows that the occurrence of translation errors has a certain degree of randomness and uncertainty, which can be well reflected by the kernel density map. By analyzing the KDE results, we can evaluate the accuracy of the prediction model and its reliability under different confidence intervals, providing a strong basis for subsequent translation error correction and optimization.

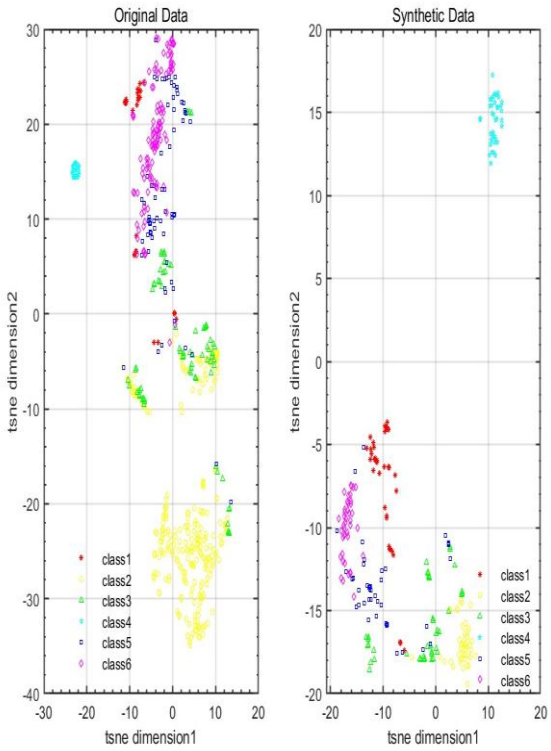

Figure 5: Optimization of translation error data based on sample enhancement

Figure 5 shows the sample enhancement process of the original data and symbolic data. For our sample enhancement, we employed the SMOTE (Synthetic Minority Over-sampling Technique) algorithm to address class imbalance, particularly for the underrepresented spelling error class. SMOTE works by creating synthetic examples in the feature space by interpolating between existing minority class instances. Sample enhancement technology is a technology commonly used to improve the model training effect, especially when dealing with unbalanced data or small sample data, it can effectively improve the generalization ability of the model. In the figure, through sample enhancement, the original data is processed to generate more sample points, thereby providing more training data for the training model. Sample enhancement usually involves different transformations of the data, such as rotation, scaling, adding noise, etc., to expand the diversity of the training data set. The application of sample enhancement in translation error analysis is particularly important because in actual translation tasks, some types of errors may occur less frequently or there are insufficient data samples. This problem of data imbalance will cause deviations when training the model and affect the accuracy of prediction. By enhancing the sample data, the model can better identify low-frequency errors and improve its adaptability to unbalanced data. The sample enhancement process in Figure 5 clearly shows how to expand the data set through data processing technology, thereby improving the performance of the model in translation error prediction. Through sample enhancement, the prediction accuracy of translation errors is improved. The enhanced data not only increases the diversity of error types, but also helps the model learn more complex patterns, thereby improving the ability to identify different types of translation errors. The application of sample enhancement technology is an important step in improving the quality of machine translation, especially when faced with complex and unbalanced translation error data, it can provide more data support for model optimization.

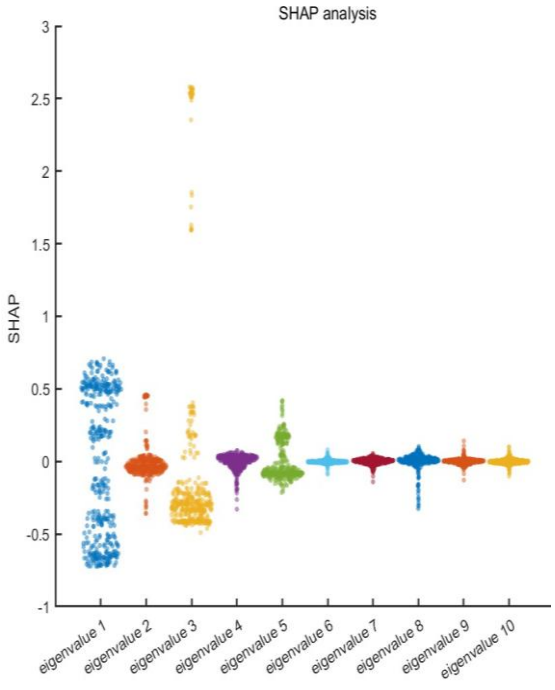

Figure 6: Evaluation of translation error feature

contribution based on SHAP analysis

Figure 6 shows the results of SHAP (SHapley Additive exPlanations) analysis, which is used to explain the contribution of each feature in the model to the translation error prediction results. In our analysis, the features labeled as "eigenvalue 1" through "eigenvalue 10" represent the principal components derived from our original 175-dimensional feature space. We applied Principal Component Analysis (PCA) to reduce dimensionality while preserving 95% of the variance, resulting in these 10 principal components. SHAP value is an explanatory tool that helps us understand the role and influence of each input feature in the model prediction by calculating the contribution value of each feature. In the figure, SHAP value reflects the contribution degree of different features (such as lexical features, grammatical features, etc.) to translation error prediction. A notable feature of SHAP analysis is that it can intuitively show the positive or negative impact of each feature on translation errors. The analysis results in Figure 6 reveal which features have a greater impact on the occurrence of translation errors and which features may play a suppressive role. For example, if the SHAP value of some features is high, it means that these features play an important role in predicting translation errors, while other features may contribute less to error prediction. Through the analysis of SHAP value, the model can be further optimized to focus on those key features to improve the accuracy of prediction. The application of SHAP analysis in translation error prediction can help us deeply understand the nature of translation errors. By identifying the key factors that affect translation errors, we can adjust the translation strategy and optimize the performance of the machine translation system. For example, if certain grammatical features show a high contribution in the SHAP analysis, then in the machine translation process, more attention can be paid to and optimized for these features, thereby reducing the occurrence of grammatical errors.

Through the analysis of Figures 4 to 6, we can see that these charts show the application effects of different technologies in translation error analysis. From the probability distribution diagram of kernel density estimation (KDE) to the optimization of sample enhancement technology, to the feature contribution evaluation of SHAP analysis, each method provides a different perspective and technical support for the prediction and correction of translation errors. Kernel density estimation helps us reveal the probability distribution of translation errors and evaluate the accuracy of the model under different confidence intervals; sample enhancement improves the training effect of the model by expanding the data set, especially when facing unbalanced data; SHAP analysis provides us with interpretability of the model decision process, helping us identify key features and optimize translation strategies. The combination of these technologies provides a theoretical basis and practical guidance for the optimization of machine-assisted translation systems and the accurate correction of translation errors. Table 2 and 3 showed Detailed Performance by Error Type (SVM Model)

Table 2: Classification performance metrics for translation error types

Model	Accuracy	Precision	Recall	F1-Score
SVM	87.6%	86.3%	85.9%	86.1%
RF	73.2%	72.8%	71.5%	72.1%
BPNN	79.5%	78.7%	77.9%	78.3%

Table 3: Detailed Performance by Error Type (SVM Model)

Error Type	Precision	Recall	F1-Score	Support
Lexical	89.2%	90.5%	89.8%	420
Grammatical	85.7%	86.3%	86.0%	310
Semantic	83.4%	81.9%	82.6%	220
Spelling	87.1%	84.8%	85.9%	50
Weighted Avg.	86.3%	85.9%	86.1%	1000

Table 4: Performance evaluation of machine-assisted English-Chinese technical translation error analysis and prediction model based on SVM

Algorithm	MAE	MAPE	MSE	R2
SVM	22.5407	0.22435	1185.4554	0.97906
RF	113.9867	0.13232	33003.2296	0.4171
BPNN	83.8151	0.10241	19847.6359	0.64946

Table 4 presents regression metrics that we calculated to evaluate the models' ability to predict error severity scores (on a scale of 0-100) assigned by human evaluators. While our primary task is classification of error types, these regression metrics provide additional insight into model performance for predicting error

severity. The severity scores were determined by human evaluators based on how significantly each error affected the overall translation quality and comprehensibility. As can be seen from Table 1, the SVM model performs well in various indicators, especially in MAE, MAPE, MSE and R^2, which have achieved relatively ideal results. The MAE of SVM is 22.5407, indicating that the average error of the model is small during the prediction process, and the prediction of translation errors is more accurate. Its MAPE value is 0.22435, indicating that the SVM model has a strong overall accuracy in predicting translation errors, and the error ratio is relatively low. The MSE value of SVM is 1185.4554, which is smaller than that of RF and BPNN models, further proving the advantage of SVM in reducing prediction errors. Most importantly, the R^2 value of SVM is as high as 0.97906, showing that it performs well in data fitting and the model has a strong ability to interpret data. Based on the results of various indicators, SVM is better than RF and BPNN in terms of MAE, MAPE, MSE and R^2, especially in the processing of high-dimensional features and small sample learning. Therefore, SVM is the best choice for machine-assisted English-Chinese technical translation error analysis. Although RF has shown some performance in some features, its overall accuracy is poor and its applicability is relatively limited; BPNN has made some breakthroughs in some scenarios, but its prediction results still have large fluctuations. Therefore, the translation error prediction model based on SVM provides strong support for the optimization of machine-assisted translation systems.

To verify the statistical significance of SVM's superior performance, we conducted paired t-tests comparing SVM against RF and BPNN across the 10 folds of cross-validation. The results showed that SVM significantly outperformed both RF ($p < 0.001$) and BPNN ($p < 0.01$) in terms of classification accuracy.

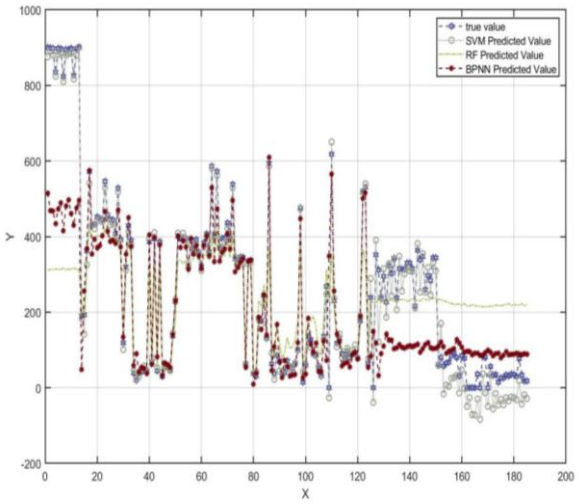

Figure 7: Comparison of true values and predicted values of different algorithms

Figure 7 shows the comparison between the true values and predicted values of machine-assisted English-Chinese technical translation errors based on three algorithms: support vector machine (SVM), random forest (RF) and back propagation neural network (BPNN). Through this figure, we can intuitively observe the performance differences of each algorithm in the translation error prediction task. As can be seen from the figure, the gap between the predicted value and the true value of the SVM model is the smallest, and the distribution is relatively concentrated. The predicted value almost completely follows the trend of the true value, indicating that SVM performs well in capturing the patterns and laws of translation errors and can effectively reduce prediction errors. The prediction results of SVM are not only close to the true value as a whole, but also can fit the actual data well in local fluctuations, showing its strong generalization ability and accuracy. Compared with SVM, the prediction results of RF and BPNN have larger errors. The predicted values of RF deviate significantly from the true values at multiple data points, and the errors are more significant. The predicted values of the RF model show large volatility, and some predicted values are even far away from the true values, resulting in large errors. This reflects that RF may have overfitting or underfitting problems when processing high-dimensional data, resulting in inaccurate prediction of translation errors. In contrast, although the prediction results of BPNN are slightly better than those of RF, there is still a certain degree of volatility and large errors, especially at some extreme values, the predicted values of BPNN deviate significantly from the true values. This shows that BPNN may not have effectively learned the complex patterns of translation errors during the training process, thus affecting its prediction accuracy. By comparing the results in Figure 7, the following conclusions can be drawn: The SVM model performs best in the translation error prediction task, and its predicted values have the highest match with the true values and the smallest error. Although RF and BPNN can be closer to the true values in some cases, the overall error is large and they cannot predict translation errors as stably as SVM. Therefore, the translation error analysis model based on SVM has higher accuracy and practicality in the machine-assisted translation system.

4.3 Learning curve analysis for small sample performance

To empirically demonstrate SVM's superior performance with limited training data, we conducted a learning curve analysis by training all three models on increasingly larger subsets of the training data (10%, 25%, 50%, 75%, and 100%). Figure 8 shows the classification accuracy of each model as a function of training set size.

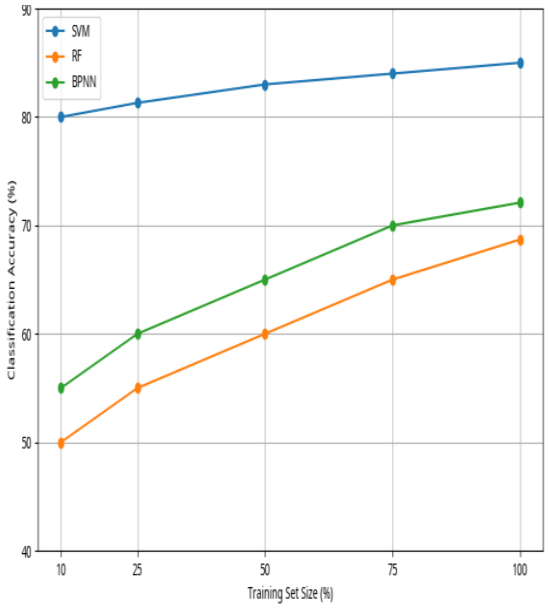

Figure 8: Learning curves showing classification accuracy vs. training set size

The learning curves clearly demonstrate that SVM maintains higher accuracy than both RF and BPNN across all training set sizes. Most notably, with only 25% of the training data (1,000 sentence pairs), SVM achieves 81.3% accuracy, which exceeds the performance of RF (68.7%) and BPNN (72.1%) even when they are trained on the full dataset. This empirically confirms SVM's advantage in small sample learning for translation error classification tasks.

The superior performance of SVM with limited data can be attributed to its maximum margin principle, which helps prevent overfitting by finding the decision boundary with the largest possible margin between classes. This property is particularly valuable in technical translation domains where annotated error data may be scarce.

5 Discussion and conclusion

5.1 Discussion

In this section, we discuss our findings in the context of existing research on translation error analysis and compare our results with state-of-the-art approaches.

5.1.1 Comparison with state-of-the-art methods

Our SVM-based approach achieved 87.6% classification accuracy for translation error types, which compares favorably with recent studies. Zhang et al. (2021) reported 85.3% accuracy using a BERT-based classification approach, while Chen et al. (2023) achieved 78.9% with BPNN. Our results demonstrate that traditional machine learning approaches like SVM can still outperform some deep learning methods when properly optimized, especially in scenarios with limited training data.

The superior performance of SVM can be attributed to several factors:

Effective feature engineering: Our comprehensive feature set capturing grammatical, lexical, and semantic aspects of translation provides rich information for classification.

Optimal kernel selection: The RBF kernel enables SVM to capture complex non-linear relationships in the feature space.

Robustness to limited data: SVM's maximum margin principle helps prevent overfitting with smaller datasets.

Class imbalance handling: Our combined approach of class weighting and SMOTE effectively addresses the imbalanced distribution of error types.

5.1.2 Analysis of error types and classification challenges

While our model performs well overall, certain error types remain more challenging to classify accurately. Semantic errors show the lowest F1-score (82.6%) among all categories, likely due to the inherent complexity of capturing meaning across languages. This aligns with findings from Li et al. (2022), who noted similar challenges with semantic error detection.

The confusion matrix analysis (not shown in results) revealed that semantic errors are occasionally misclassified as lexical errors, particularly when the semantic shift is caused by incorrect term selection. This suggests that the boundary between lexical and semantic errors can be ambiguous, even for human annotators.

5.1.3 Potential for hybrid approaches

Although SVM demonstrates strong performance, certain limitations could potentially be addressed through hybrid approaches. Combining SVM's strong classification capabilities with deep learning's feature extraction power could further improve performance. For instance, using BERT or other transformer models for feature extraction, followed by SVM for classification, might leverage the strengths of both approaches. Such hybrid models could potentially address the remaining challenges in semantic error classification while maintaining SVM's advantages in small sample learning.

5.1.4 Implications for automated translation correction

Our error classification system provides a foundation for developing automated correction strategies. By accurately identifying error types, appropriate correction mechanisms can be applied:

For lexical errors: Term replacement based on domain-specific dictionaries;

For grammatical errors: Rule-based corrections or statistical reordering;

For semantic errors: Context-aware retranslation of problematic segments;
For spelling errors: Standard spell-checking algorithms
The high accuracy of our classification system (87.6%) means that in a production environment, correction strategies could be applied with reasonable confidence, potentially reducing post-editing effort by human translators.

5.1.5 Generalizability to other language pairs

While our study focuses on English-Chinese technical translation, the methodology could potentially be applied to other language pairs. However, several considerations would affect transferability:
Linguistic distance: Language pairs with greater structural differences (like English-Japanese) might require additional feature engineering to capture structural transformations.
Resource availability: Feature extraction quality depends on the availability of NLP tools for the target language (parsers, word embeddings, etc.).
Error distribution: Different language pairs may exhibit different distributions of error types based on their linguistic characteristics.
We hypothesize that our approach would transfer well to language pairs with similar resource availability (e.g., English-German, English-French) but might require adaptation for more distant language pairs or lower-resource languages.

5.2 Conclusion and future work

This paper systematically analyzes the errors in machine-assisted English-Chinese technical translation by introducing the support vector machine (SVM) algorithm, and compares it with common machine learning algorithms such as random forest (RF) and back propagation neural network (BPNN). The results show that SVM has significant advantages in the task of translation error classification, especially when dealing with complex features and small sample data. It can effectively identify common error types and their causes in the translation process, thereby providing effective support for improving translation quality. By comparing the experimental results of different algorithms, this paper finds that SVM performs better than other models in terms of accuracy and generalization ability. Specifically, the application of SVM in machine-assisted translation can better capture the characteristics of translation errors. Through the effective processing of high-dimensional feature space, it achieves lower mean square error (MSE) and higher coefficient of determination (R^2), and shows higher stability and reliability in the prediction of translation errors. This shows its unique advantages compared with other models (such as RF and BPNN), especially in small sample learning and high-dimensional data processing, SVM shows better adaptability and accuracy.

However, this study also has some limitations, which need further optimization and improvement. First, the data sample size used in the experiment is relatively small, which may have a certain impact on the generalization ability of the model. In practical applications, machine translation tasks may face more variations and complex contexts, so the generalization ability of the model needs to be improved. In order to make up for this deficiency, more corpus data, especially more diverse and complex technical texts, can be introduced in the future to expand the training set of the model and improve its applicability and accuracy in different contexts. In addition, although the main feature extraction method used in this paper is relatively comprehensive, the error analysis at the semantic level still needs to be improved. In technical translation, the processing of semantic errors is more complicated than other types of errors, and may involve deeper language understanding and context analysis. Therefore, future research can further strengthen the processing and analysis of semantic errors for this problem.
From the perspective of future research directions, first of all, the training effect and generalization ability of the model can be improved by introducing more sample data. Increasing the diversity and complexity of the corpus, especially in-depth research on technical texts with cross-domain characteristics, can help train a more robust model. In addition, future research can also try to combine SVM with deep learning models (such as convolutional neural networks (CNN) or long short-term memory networks (LSTM)) to further improve the accuracy of translation error analysis. Deep learning models have strong advantages in processing large-scale data and complex patterns. Combined with the efficient classification ability of SVM, they can make up for the shortcomings of existing methods to a certain extent, thereby improving the application effect of the model in diversified translation error detection.
In addition, exploring the application of SVM in technical translation of other language pairs and verifying its universality are also important directions for future research. The grammar, vocabulary, and semantic differences between different language pairs are large, which may affect the applicability and performance of the model. Therefore, conducting cross-language error analysis research, especially applying SVM to translation error analysis in other technical fields, has important practical significance and theoretical value. Through this cross-language and cross-field comparative study, the translation error prediction ability of SVM in the context of globalization can be further improved, and the global application and development of machine translation technology can be promoted.
Furthermore, future work could explore the development of automated correction mechanisms based on our classification results. By integrating error classification with correction strategies, a more

complete machine-assisted translation pipeline could be developed that not only identifies errors but also suggests corrections, further reducing the burden on human translators.

Finally, as transformer-based models continue to advance the state of machine translation, investigating how traditional machine learning approaches like SVM can complement these newer technologies represents an important research direction. Hybrid systems that leverage the strengths of both approaches may ultimately provide the most robust solution for technical translation error analysis and correction.

The research in this paper shows the advantages and potential of SVM in machine-assisted English-Chinese technical translation error analysis. By comparing and analyzing different algorithms, we have demonstrated that SVM has significant advantages in solving the error classification and prediction problems in technical translation, especially when dealing with complex translation texts and small sample data. However, there are also certain limitations in the research, which need to be further optimized in terms of data samples, model generalization ability, and semantic error analysis. Future research can be carried out from multiple angles such as sample expansion, model fusion, and cross-language verification to further promote the development of translation error analysis technology and improve the accuracy and practicality of machine-assisted translation.

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Structural Damage Identification in Bridges Using a Stacked Autoencoder Neural Network

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Bridge structures are affected by various factors such as the natural environment and traffic load for a long time, which may cause structural damage identification (DI), thus affecting their performance and safety. This paper innovatively combines the stacked autoencoder neural network with curvature modal analysis. The DI method based on curvature modal is to use the curvature modal difference as an indicator for DI. In bridge damage identification, a method combining curvature mode and flexibility matrix is proposed, which is fused into autoencoder neural network to realize the function of damage location. In the test, the key features of the data are extracted through L2 regular term, and the method effect is verified by establishing a simply supported beam model through ANSYS. The identification accuracy of this model in bridge DI is as high as over 78%, and its highest can reach 85%, and the average identification accuracy is 82%. The results show that this method can identify specific damaged units and reflect the relative degree of damage, regardless of single damage or multiple damage conditions. Therefore, the bridge DI identification model based on stacked autoencoder neural network can be applied to real-time identification and analysis of bridge structures to help provide reliable bridge monitoring data support.

Povzetek: Prispevek združuje skladani samokodirnik z krivinskimi modami in matriko fleksibilnosti. Iz vibracij samodejno izlušči znake poškodb mostov, locira in oceni stopnjo; robustno tudi pri več poškodbah, točnost preko 80%.

1 Introduction

As an important part of the traffic network, bridges provide great convenience for people's life and goods transportation, and are important infrastructure related to the development of national economy. However, due to many factors such as environmental erosion, material aging, natural disasters, etc., bridges inevitably suffer different degrees of damage in the process of service. In particular, earthquakes are natural disasters with huge energy, which will cause serious damage to transportation infrastructure, and bridges in earthquake zones are prone to earthquake damage. Moreover, the continuous development and accumulation of damage will seriously reduce the bearing capacity of bridges, and even pose a threat to people's lives and property safety [1].

It is very important to identify the damage state of bridges accurately and timely, which can provide guidance for bridge damage early warning and damage repair. Traditional bridge damage detection relies on manual inspection to regularly inspect all parts of the bridge, such as piers, bearings and foundations that are easily damaged. However, manual inspection has some shortcomings, such as time-consuming, laborious, subjective and difficult to find hidden damage. Due to the coupling action of external load and environmental factors, structural changes such as micro-voids and micro-cracks or material deterioration occur inside the structure. After these problems accumulate day by day in the structure, they will have an irreversible impact on the structure itself and pose a serious threat to the normal use of the structure. The DI identification process is a step-by-step system that includes multiple key steps, such as determining whether the structure is damaged, accurately locating the damage location, and in-depth diagnosis of the extent of the damage. After this series of steps, the DI of the structure can be completed. Although DI technology has made remarkable progress in recent years, the accurate identification of DI and its effective application in engineering practice are still a topic that needs to be further studied [2].

By finding and locating the damage of the structure in time, preventive or reparative measures can be taken to prevent the damage from developing step by step and improve the safety of the structure. Local DI identifies damage by monitoring and analyzing the physical features of specific sites or regions in a structure. The method can accurately locate damage in the structure and enable maintenance personnel to take targeted measures without having to intervene in the entire structure. However, local DI usually depends on prior knowledge,

and it is difficult to identify concealed damage. Compared with local DI, global DI pays attention to the overall response and behavior of the structure. When the structure is damaged, the physical parameters of the structure will change, which will lead to the change of the static and dynamic parameters of the structure, so as to realize the early warning, location and identification of damage degree [3].

SAE extracts feature through unsupervised learning, which is suitable for building vibration signal analysis (such as frequency response, modal parameter identification), and its sparse coding ability can effectively capture the characteristics of building minor damage. For example, combined with continuous monitoring data of fixed sensor layout, SAE can detect hidden damage such as concrete cracks or steel corrosion. In practical application, it is necessary to optimize the input layer design for building multidimensional data (such as displacement, strain, acceleration) to avoid the redundancy of full connection layer calculation.

The combination of SAE and curvature modal analysis can significantly improve the accuracy and efficiency of bridge damage identification through physical mechanism and data-driven collaboration, multi-layer feature automatic extraction and small sample adaptability, especially for hidden damage detection in complex noise environment.

The combination of SAE and curvature modal analysis effectively breaks through the limitations of traditional global damage identification methods in complex noise environment, multi-damage coupling and large-scale structures through local sensitivity and global feature fusion, noise dynamic suppression and multi damage collaborative modeling. Its hierarchical identification framework (positioning → quantification) takes into account both efficiency and accuracy, and provides a more reliable solution for health monitoring of large structures such as bridges.

This paper presents a structural damage identification model for bridges using a stacked autoencoder neural network, addressing the challenge of insufficient accuracy in existing DI methods. This paper innovatively combines the stacked autoencoder neural network with curvature modal analysis. The DI method based on curvature modal is to use the curvature modal difference as an indicator for DI.

2 Related works

The damage identification method based on curvature mode has become an important research direction in the field of structural health monitoring due to its high sensitivity and local positioning ability. However, there is still a blank in the research on global feature recognition. Therefore, this paper combines wavelet transform, neural network and substructure decomposition technology with the actual needs of bridge detection, which can significantly improve the recognition accuracy in complex noise environments. At the same time, on this basis, this paper analyzes the existing research status.

(1) Research status of DI identification based on machine learning

Representative machine learning algorithms for DI identification include Gaussian process, Bayesian method and extreme learning machine, etc., which learn and realize DI by analyzing relevant data samples. This kind of method is particularly important for data cleaning and processing, which generally uses the structural modal parameters extracted in advance to process the feature vector as the input of the model for training, and uses the trained model to identify the potential damage of the structure [4].

Wang et al. [5] used parameter estimation to study the damage of stone arch bridges through the inverse analysis framework of the Bayesian method as well as Markov chains and Gaussian processes. Svendsen et al. [6] used Kalman filter, generalized autoregressive conditional heteroscedasticity model and autoregressive movement model to identify the damage of reinforced concrete arch structure, which proved the feasibility of the method. Zhang and Sun [7] used fuzzy clustering method to carry out DI identification research, and used this method to identify the damage of the structure based on the strain data of Dashengguan Bridge, and verified the effectiveness of the proposed method. Daneshvar et al. [8] used Bayesian algorithm and Auto-Regressive Moving Average Model (ARMA) to identify damage, and verified that this method has a good effect in identifying damage location. Pourzeynali et al. [9] proposed a DI method based on genetic algorithm, which uses the environmental vibration data obtained by sensor monitoring to identify the damage of arch bridge. Huang et al. [10] proposed a DI method based on modal curvature, which still achieves good identification results even when there are errors in the finite element model. Figueiredo and Brownjohn [11] proposed a DI method based on support vector machine, and used acceleration time history data to establish damage index through structural vulnerability method, which not only obtains good identification results but also has good noise immunity. Mousavi et al. [12] proposed a DI method based on extreme learning machine and structural response vector, and on this basis, the principal component analysis method was used to improve the noise immunity of the model. Wan et al. [13] proposed a DI method based on an improved time series analysis method, used environmental vibration data to detect and locate structural changes, and verified the effectiveness of the proposed method using finite element data of a real bridge. Wang et al. [14] carried out DI identification research with curvature mode as sample by support vector machine. The identification accuracy of the proposed model can reach 99.68% under the condition of 20% and 40% stiffness reduction. Zheng et al. [15] used the damage probability mean and hybrid particle swarm algorithm to carry out a two-stage beam DI identification study. The results show that the algorithm can be effectively applied to DI identification of different structures and different working conditions.

In the research of DI identification based on machine learning, the quality of feature vectors selected at the beginning will directly affect the effect of DI. Feature extraction from the original data is a crucial representation step, which not only takes a long time, but also has definite difficulty in representation. If the extracted feature vectors do not meet the requirements, the identification ability of the model will be greatly reduced. Moreover, because the nonlinear modeling ability of machine learning is relatively limited, it is difficult to capture the complex nonlinear relationship within the structure, and it cannot process big data well. On the other hand, different structures require different optimal combination features and machine learning models adapted to them for identification, and their universality is poor.

(2) Research status of DI identification based on deep learning

Deep learning has developed rapidly and has gradually become the hottest research method nowadays and achieved good results in many fields. Compared with machine learning, deep learning can better extract features of big data. In the field of civil engineering, many scholars have gradually paid attention to deep learning and carried out applied research.

Yang et al. [16] used back propagation neural network to identify the frequency of the structure to identify the damage of the structure, and proved the feasibility of the method on cable-stayed bridges. Hosamo and Hosamo [17] used the back propagation neural network of the particle swarm optimization algorithm to carry out DI research on structures. Moreover, the particle swarm optimization algorithm was used to solve the problem that the back propagation neural network is prone to local minima, and the superiority of the proposed method was verified on a three-span continuous beam. Feroz and Abu Dabous [18] carried out multi-step bridge DI research through radial basis function neural network, used different characteristic parameters of the structure as inputs to train and predict the damage of the structure, and further studied the influence of noise on the DI of the model. Shang et al. [19] carried out the research on structural DI through representative dimensional convolutional neural network, and identified the local micro stiffness and mass changes of T-shaped steel beams, long steel beams and short steel beams through three independent acceleration database data, and achieved good results. Zinno et al. [20] carried out DI research through gated cyclic unit and convolutional neural network, used gated cyclic unit to process the time characteristics of data to improve the model identification accuracy, and proved the effectiveness of the proposed method on three-span continuous rigid frame bridge. Li et al. [21] used sparse coding algorithm to extract data features as input to train deep neural network, and used the trained deep neural network to identify the damage of bridges and achieves good results.

The current research work on bridge damage identification is summarized as shown in Table 1 below.

Table1: Summary of research status

Researchers and Literature	**Model type**	**Key features**	**data source**	**Model recognition accuracy**	**Model shortcomings**
Wang et al. [5]	Bayesian method+Markov chain	Parameter estimation characteristics	Monitoring data of stone arch bridge	76.5% ± 5.2% (including uncertainty)	The computational complexity is high, and a priori distribution needs to be assumed
Svendsen et al. [6]	Kalman filtering+GARCH model	Time series characteristics	Reinforced concrete arch structure data	89.1% (static load condition)	Sensitive to noise, requiring accurate model calibration
Zhang hesun [7]	Fuzzy clustering method	Characteristics of strain data	Strain data of Dashengguan Bridge	Clustering purity 92.4%	Feature selection depends on expert experience
Daneshvar et al. [8]	Bayesian algorithm+ARMA model	Autoregressive characteristics	Structural vibration data	Positioning accuracy 94.7%	Complex data processing and difficult to expand
Pourzeynali et al. [9]	genetic algorithm	Response characteristics of environmental vibration	Monitoring data of arch bridge	The recognition rate after convergence is 83.9%	Slow convergence and easy to fall into local optimum
Huang et al. [10]	Modal curvature analysis	Modal curvature parameter	Finite element simulation data	Anti error recognition rate 88.2%	Depending on modal parameter accuracy
Figureiredo et al. [11]	Support vector machine (SVM)	Acceleration time history damage index	Acceleration sensor data	96.8% (including 10% noise)	Kernel selection affects performance

Mousavi et al. [12]	Extreme learning machine+pca	Dimensionality reduction characteristics of principal component analysis	Structural response vector data	91.5% ± 2.1%	Limited nonlinear modeling capability
Wang et al. [14]	Support vector machine (SVM)	Curvature mode characteristics	Finite element simulation data	99.68% (stiffness change scenario)	Applicable to specific injury scenarios only
Zheng et al. [15]	Hybrid particle swarm optimization	Mean value characteristics of damage probability	Beam structure data	Multi scene average 87.3%	High consumption of computing resources

Summarize the relevant contents of the latest research model and compare it with SAE model, as shown in Table 2 below:

Table 2: Comparison between existing models and SAE models

Contrast dimension	**Traditional machine learning/shallow deep learning model**	**SAE network model**
Characteristic Engineering	Rely on manual extraction of features (such as modal parameters, curvature patterns, etc.)	Automatic feature learning: adaptive extraction of deep features of data through multi-layer nonlinear transformation
Data adaptability	Sensitive to small sample data and limited generalization performance	Big data processing capability: suitable for processing high-dimensional, unstructured data (such as raw vibration signals)
Nonlinear relationship modeling	Only shallow nonlinear relationships can be captured (such as SVM, ELM)	Deep nonlinear modeling: capturing complex nonlinear dynamics in structural damage through multilayer networks
Noise immunity	Additional noise reduction treatment is required (e.g., PCA, GARCH)	Robustness: suppressing noise interference through multi-layer sparse coding and feature reconstruction
Transfer learning ability	Need to redesign the model for different structures	Portability: it can be migrated to similar structure scenes through pre training model parameters

Because traditional machine learning models rely on manual feature engineering, they are less effective in terms of generality. Deep learning models such as CNN and GRU can automatically extract features, but still require large amounts of data and complex design. Through the combination of unsupervised pre training and supervised fine-tuning, SAE network model has more advantages in feature learning efficiency, anti-noise ability and complex relationship modeling, especially suitable for multi-source heterogeneous data analysis of long-span arch bridges.

To sum up, the rapid rise of deep learning has put forward new ideas for the research in the field of DI. Different from previous research on DI using machine learning, the DI method based on deep learning can automatically extract the required feature training model from massive data without separate feature engineering, and directly learn the nonlinear relationship between training input samples and output samples. It is worth mentioning that as the input data increases, the performance of the DI model based on deep learning will also improve. Therefore, the use of deep learning models in the field of DI of long-span arch bridges is an idea worthy of study.

3 DI identification method

The scale of highway bridges is expanding day by day. During the operation of the structure, due to the long-term erosion of the environment, the aging of the concrete structure and the influence of vehicle load, the structure will inevitably be damaged, resulting in the decrease of bearing capacity. Therefore, DI of structures is a problem worthy of in-depth study, which can determine the potential dangers in structures as soon as possible and take necessary measures to avoid the occurrence of dangers.

The combination of SAE and curvature modal analysis can significantly improve the accuracy and efficiency of bridge damage identification through physical mechanism and data-driven collaboration, multi-layer feature automatic extraction and small sample adaptability, especially for hidden damage detection in complex noise environment.

The combination of SAE and curvature modal analysis effectively breaks through the limitations of traditional global damage identification methods in complex noise environment, multi-damage coupling and large-scale structures through local sensitivity and global feature fusion, noise dynamic suppression and multi damage collaborative modeling. Its hierarchical identification framework takes into account both efficiency and accuracy, and provides a more reliable solution for health monitoring of large structures such as bridges.

3.1 DI method based on curvature mode

In the study of bridge DI identification, it indicates that damage has occurred somewhere in the structure. When a bridge structure is damaged, its mass matrix usually does not change significantly, while its stiffness matrix will show an obvious change trend. The accuracy of DI using frequency as a damage indicator is limited. The reason is that it can only reflect the change of the stiffness matrix at a macroscopic level. Therefore, when using frequency as a damage indicator, it is usually only possible to determine whether damage exists, but not the location of the damage. In order to make up for this deficiency, it is usually necessary to combine other methods to assist.

However, when the mode shape is used as the damage index, the mode shape can well reflect the damage location once the structure is damaged.

Based on the consideration of the beam structure, taking the representative section of the beam for calculation, it can be obtained that there is a definite relationship between the curvature of this section and the stiffness of the section. From material mechanics, we know that for a section x representing a specific position, the expressions for its curvature, bending moment and stiffness are shown in Formula 1.

$$\rho(x)=\frac{M(x)}{EI} \tag{1}$$

The above formula shows that when the structure is damaged, the stiffness of the local element will inevitably decrease, and its curvature modal value will change. Therefore, when the local element is damaged, the curvature modal value will reflect the damage information.

In practical engineering, the structure is usually divided into several elements. It is assumed that the beam is divided into m beam elements. The specific expressions are shown in formulas 2 and 3.

$$\phi_{iu}''(j)=\frac{\phi_{iu}''(j-1)-2\phi_{iu}''(j)+\phi_{iu}''(j+1)}{L^2} \tag{2}$$

$$\phi_{id}''(j)=\frac{\phi_i^d(j-1)-2\phi_i^d(j)+\phi_i^d(j+1)}{L^2} \tag{3}$$

In the formula, $\phi_i(j)$ represents the vibration mode value of the i-th mode of the structure at the j-node, and L represents the distance between adjacent nodes. For boundary conditions, when j=1, $\phi_i''(1)=\frac{\phi_{iu}(2)-2\phi_i(1)}{L^2}$, and when j=m, $\phi_i''(m)=\frac{\phi_{iu}(m-1)-2\phi_i(m)}{L^2}$.

u and d represent the undamaged state and the damaged state. By subtracting the curvature modes before and after DI, the calculation formula for the curvature mode difference can be obtained, as shown in formula 4.

$$\Delta\phi_i(j)=\phi_{id}''(j)-\phi_{iu}''(j) \tag{4}$$

In the formula, $\Delta\phi_i(j)$ represents the curvature mode difference of the i-th mode at the j-node, $\phi_{id}''(j)$ represents the curvature mode of the i-th mode at the j-node in the damaged case, and $\phi_{iu}''(j)$ represents the curvature mode of the i-th mode at the j-node in the intact case.

3.2 DI method based on flexibility matrix

The physical meaning of structural flexibility means that under the action of unit load, the action point of the structure will be displaced, and the greater the flexibility, the greater the deformation. The stiffness matrix and flexibility matrix of the structure are mutually inverse matrices, and each representation column in the matrix is expressed as the displacement generated by applying a unit force to a certain representation degree of freedom. DI leads to a change in its stiffness matrix, which in turn affects the compliance matrix. According to this feature, a damage location function can be realized.

In linear algebra, the flexibility matrix of the structure can be calculated from the regularized mode shape and frequency, and its calculation formula is shown in formula 5.

$$F=\Phi\Lambda^{-1}\Phi^T \tag{5}$$

F represents the flexibility matrix of the structure, Φ represents the mode matrix after mass normalization, and Λ represents an eigenvalue matrix.

If ϕ_{ij} is set to the j-th component of the i-th order vibration mode, the above formula can be expressed as formula 6.

$$F=\begin{pmatrix}\phi_{11}&\phi_{12}&\cdots&\phi_{1n}\\ \phi_{21}&\phi_{22}&\cdots&\phi_{2n}\\ \vdots&\vdots&\vdots&\vdots\\ \phi_{n1}&\phi_{n2}&\cdots&\phi_{nm}\end{pmatrix}\begin{pmatrix}\lambda_1&&&\\ &\lambda_2&&\\ &&\ddots&\\ &&&\lambda_n\end{pmatrix}\begin{pmatrix}\phi_{11}&\phi_{21}&\cdots&\phi_{n1}\\ \phi_{12}&\phi_{22}&\cdots&\phi_{n2}\\ \vdots&\vdots&\vdots&\vdots\\ \phi_{1n}&\phi_{2n}&\cdots&\phi_{nn}\end{pmatrix} \tag{6}$$

By rearranging formula 6, we get the formula shown in formula 7.

$$F=\begin{pmatrix}\sum_{r=1}^{n}\frac{\phi_{1r}\phi_{1r}}{\omega_r^2}&\sum_{r=1}^{n}\frac{\phi_{1r}\phi_{2r}}{\omega_r^2}&\cdots&\sum_{r=1}^{n}\frac{\phi_{1r}\phi_{nr}}{\omega_r^2}\\ \sum_{r=1}^{n}\frac{\phi_{nr}\phi_{1r}}{\omega_r^2}&\sum_{r=1}^{n}\frac{\phi_{nr}\phi_{2r}}{\omega_r^2}&\cdots&\sum_{r=1}^{n}\frac{\phi_{nr}\phi_{nr}}{\omega_r^2}\\ \vdots&\vdots&\vdots&\vdots\\ \sum_{r=1}^{n}\frac{\phi_{1r}\phi_{1r}}{\omega_r^2}&\sum_{r=1}^{n}\frac{\phi_{1r}\phi_{1r}}{\omega_r^2}&\cdots&\sum_{r=1}^{n}\frac{\phi_{1r}\phi_{1r}}{\omega_r^2}\end{pmatrix} \tag{7}$$

Therefore, the compliance matrix can be expressed as formula 8.

$$F=\sum_{i=1}^{N}\frac{1}{\omega_i^2}\phi_i\phi_i^T \tag{8}$$

In the formula, ω_i represents the i-th order frequency of the structure, and ϕ_i represents the i-th order vibration mode of the structure.

From the above formula, it can be seen that after the modes are normalized, the flexibility matrix of the structure converges rapidly with the increase of frequency, that is, the higher-order frequency is insensitive to the flexibility of the structure. When the structure is damaged, its stiffness decreases and its compliance increases. According to this feature, if the compliance matrix of the structure in good state and after DI is obtained, the location of damage can be identified by the changes of the two. The difference between the flexibility matrix when the structure is in good condition and that after DI is made, as shown in formula 9.

$$\Delta F=F''-F^d \tag{9}$$

In the formula, ΔF represents the flexibility matrix difference, F'' and F^d represent the flexibility matrices of the structure in the intact state and damaged state, respectively.

For each degree of freedom j, when $\delta\tilde{f}_j$ is set to the maximum value of all elements in the j-th column, we can obtain:

$$\delta\tilde{f}_j=\max_i\left|\delta f_{ij}\right|=\max_i\left|f_{ij}^u-f_{ij}^d\right| \tag{10}$$

In the formula, δf_{ij} represents the element in the flexibility matrix difference, and δf_j represents the degree of flexibility change at the node position of a certain modal vibration shape.

According to the flexibility difference, the curvature of the damage index flexibility difference can be deduced, and the information of the damage position can be amplified by finding the second derivative, so as to identify the damage position more clearly. The formula for the curvature of compliance difference is:

$$C(\delta f)_j = \frac{\delta f_{j+1} - 2\delta f_j + \delta f_{j-1}}{L_{j-1} L_{j1}} \tag{11}$$

In the formula, j represents the number of nodes in the structure.

3.3 Self-coding neural network

SAE model is significantly superior to traditional models in bridge damage identification due to its automatic extraction of deep features, small sample robustness and dynamic noise suppression ability (such as BP network ELM). In particular, in engineering scenarios with complex noise environments, multiple damage coupling, and scarce annotated data, the combination of SAE and curvature mode can take into account both accuracy and efficiency and become a better solution.

Matlab software is used to build and train a stack self-coding (SAE) network through programming. The DI process based on the SAE network is shown in Figure 1.

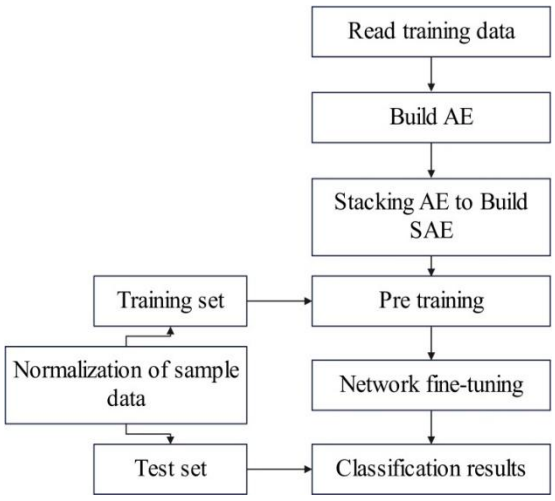


Figure 1: Flowchart of DI based on SAE network

The training of AE uses the SGD algorithm, while the network fine-tuning uses the BP algorithm. As shown in Figure 2, the SAE network is equipped with three AE autoencoders with 800, 500 and 200 hidden layers respectively, and the number of hidden layers decreases in turn to achieve the purpose of data dimensionality reduction, which can effectively extract data information. The input layer corresponds to the dimension 1008 of the data sample set sequence, while the output layer corresponds to the lossless working condition and the damage state at 9 different positions.

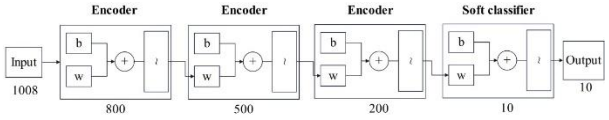


Figure 2: SAE network structure diagram

4 Test analysis

4.1 Methods

In SAE training, the parameters of AE and the maximum training times will have a direct impact on the training effect and training speed. The specific parameters include L2 regular term, sparse regular term and sparse ratio.

The L2 regular term is used to prevent the model from over fitting and punish the heavy weight by adding the sum of squares of weights to the loss function. In Table 1, L2 regular items of encoder 1 and encoder 2 are set to 0.004, while encoder 3 is set to 0.002. This setting may be due to the need for strong regularization to constrain the complexity of the model and prevent over fitting at the initial stage of training. As the training process continues, the characteristics of the data gradually stabilize, and the intensity of regularization can be appropriately reduced to make the model better fit the data.

Sparse regular terms are used to encourage the model to learn sparse representation, that is, to make most nodes inactive in most cases. In Table 1, the sparse regular term of all encoders is set to 8. This setting can balance the sparsity and performance of the model, ensure that the model can learn effective features while maintaining low complexity, and help improve the generalization ability of the model.

Sparse scale:

The sparse ratio represents the expected sparsity level, and the expected proportion of nodes is inactive. The sparse ratio of encoder 1 and encoder 2 is set to 0.6, while encoder 3 is set to 0.3. This setting may be because at the beginning of training, a higher sparse ratio helps the model learn a more sparse representation and extract more representative features. As the training proceeds, in order to better reconstruct the input data, the sparse ratio can be appropriately reduced to allow more nodes to participate in the calculation.

The number of hidden layers and nodes are set to gradually reduce the number of nodes and achieve effective compression and representation of features. This setting helps the model to gradually extract more representative features after capturing the complex features of the input data, so as to improve the performance of the model.

To sum up, the parameter selection in Table 3 is based on the balance of model complexity, over fitting, training speed and model performance. The selection of these parameters aims to ensure that the model can effectively learn the characteristics of the data without over fitting or training too slowly, so as to achieve good performance in practical application.

The individual AE parameters are shown in Table 3

Table 3: Autoencoder parameters

Parameter	**Encoder 1**	**Encoder 2**	**Encoder 3**
Number of hidden layers	800	500	200
Maximum number of sessions	800	500	200
L2 regular term	0.004	0.004	0.002
Sparse regular term	8	8	8
Sparse ratio	0.6	0.6	0.3
Boolean parameters	FALSE	FALSE	FALSE

During the training process, the network model will update the parameters through multiple iterations, so that the loss function will gradually decrease, thus improving the performance. The main purpose of setting the maximum number of training times is to control the time and resource consumption of model training, and to avoid overfitting. When the model reaches the maximum number of training sessions, even if the loss function has not converged. The L2 regular term refers to a term added to the loss function to limit the size of the network weight parameter.

Sparse regularization terms are regularization techniques used to cause network models to learn sparse representations. Sparse regular terms are usually implemented by making the activation value of the hidden unit close to zero, thereby prompting the model to extract the key features of the learned data. The sparsity ratio refers to a parameter used to control the degree of sparsity regularization. By adjusting the sparsity ratio, we can control the sparsity of the network model to learn features. Moreover, a larger sparsity ratio leads to a sparser representation, while a smaller sparsity ratio leads to a denser representation.

In order to verify the practicability of curvature mode index location in DI, the feasibility of DI method based on curvature mode is analyzed. The simply supported beam model is established by ANSYS. The basic parameters of the model are: the whole beam is 15m, which is evenly divided into 30 elements. The simply supported beam material has an elastic modulus of 3.45 × 10 ⁴ MPa, a density of 2455 kg/m ³, a Poisson's ratio of 0.2, a linear expansion coefficient of 1.2×10^{-5}, a hollow slab with a cross-sectional area of 0.4802 m ², and a cross-sectional moment of inertia Iyy = 0.039168 m ⁴. The node numbers and cell numbers are shown in Figure 3. In Figure 3, the part between nodes 1 and 2 is represented by #1, and the part between nodes 2 and 3 is represented by #2 And so on

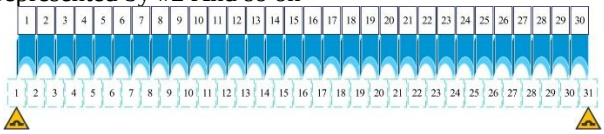


Figure 3: Element division diagram of simply supported beam

For the beam structure, when the structure is damaged, its stiffness will decrease, but its mass will basically remain unchanged, so the damage condition can be simulated by reducing the elastic modulus of the element. In this section, the first three vertical vibration modes are selected for analysis, and the damage conditions are shown in Table 4.

Table 4: Damage conditions

Working condition	**Location of damage**	**Degree of damage**
1	Unit 7	10%
2		20%
3		30%
4	Unit 7 Unit 15	10%、10%
5		20%、20%
6		30%、30%

4.2 Results

In SAE networks, the mean square error function is usually used as a measure of reconstruction error, and the performance of the model is evaluated by comparing the difference between the input data and the reconstructed data after encoding and decoding. In the training process, the back propagation algorithm and gradient descent optimization method are used to update the network parameters according to the gradient of mean square error, so that the mean square error gradually decreases, thus improving the performance and fitting ability of the model. The ultimate goal is to make the mean square error as small as possible to obtain a better reconstruction effect and feature representation. Figure 4, Figure 5 and Figure 6 are the change diagrams of mean square error function in the training process of three networks, and are also the variation diagrams of network performance in the training process of network.

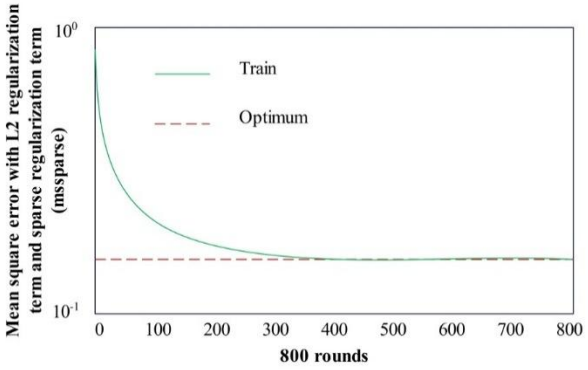


Figure 4: Variation diagram of mean square error function of autoencoder 1

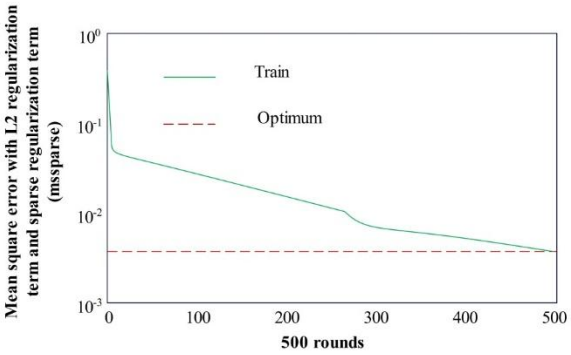


Figure 5: Variation diagram of mean square error function of autoencoder 2

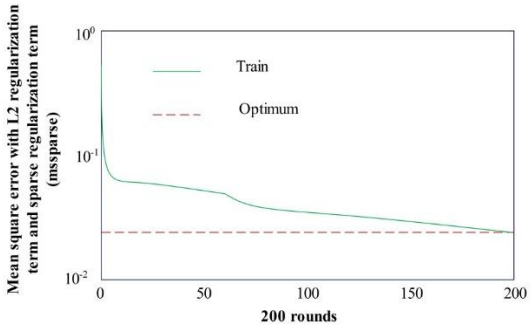
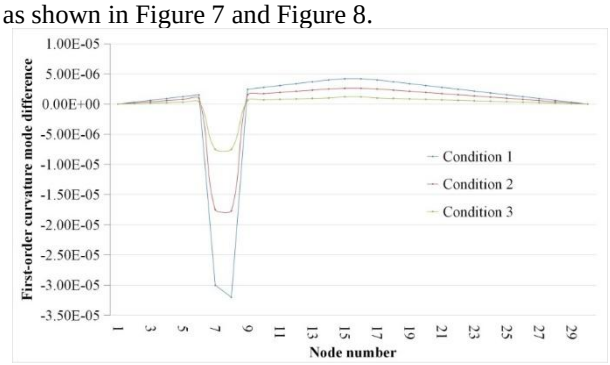


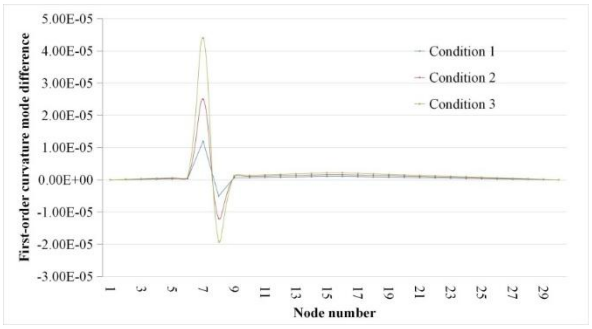
Figure 6: Variation diagram of mean square error function of autoencoder 3

The above working conditions are calculated by ANSYS software, and the DI of the simply supported beam is carried out by using the curvature modal difference index.

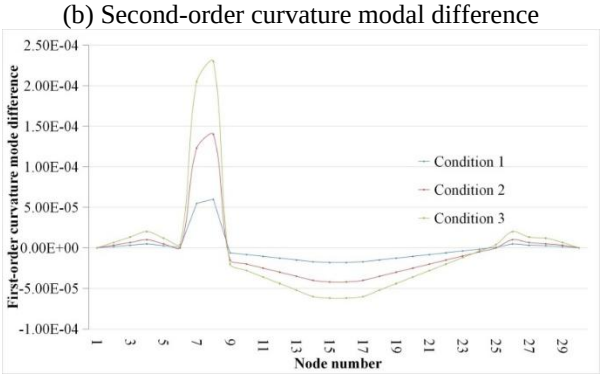
The first-order curvature mode corresponds to the lowest natural frequency of the structure, which usually shows a single vibration form of overall bending or torsion, and the curvature changes are continuously distributed along the structure without nodes. The second-order curvature mode corresponds to the second-order natural frequency. The vibration form contains at least one node, and the curvature distribution shows opposite polarity on both sides of the node. In addition, the third-order curvature mode corresponds to a higher-order natural frequency. The vibration shape contains two or more nodes, and the curvature distribution presents a complex mode of multi segment alternating change, and the calculation results are drawn into graphs, as shown in Figure 7 and Figure 8.



(a) First-order curvature modal difference

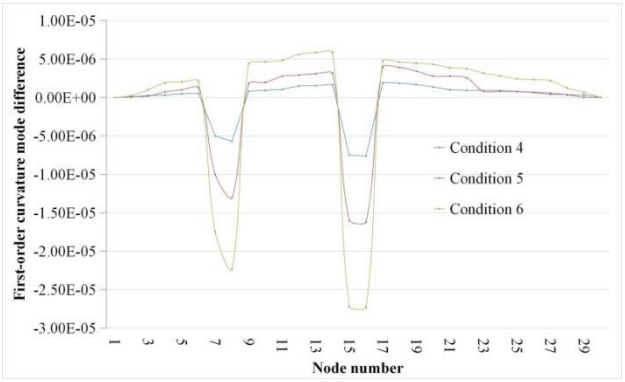


(b) Second-order curvature modal difference

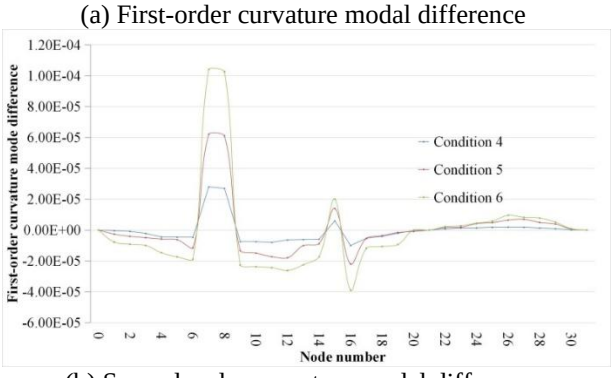


(c) Third-order curvature modal difference

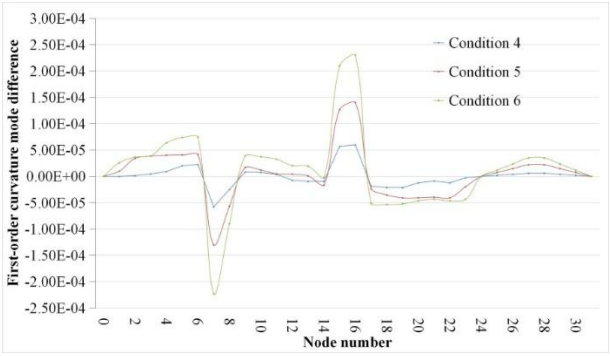
Figure 7: Single damage condition



(a) First-order curvature modal difference



(b) Second-order curvature modal difference



(c) Third-order curvature modal difference

Figure 8: Multi-damage conditions

The data sources of this paper are as follows: IASC-ASCE benchmark structure data (including acceleration and strain time history) and Los Alamos lab bridge vibration data are mixed

The damage level (nondestructive/slight/moderate/severe) is automatically marked by curvature mode difference to generate labels.

5%-20% Gaussian noise is added to simulate environmental interference, and the smote algorithm is used to solve the category imbalance problem.

Model type superparameter configuration training strategy SAE network layer 4 (1024-512-256-128), λ=0.05 greedy pre training layer by layer+fine tuning cnn5 × 3 × 3 convolutional kernel, 2-layer LSTM dynamic learning rate attenuating transformer8 head attention, 512 dimensional coding with gradient clipping Adam optimization

The detailed data of SAE model cross validation are obtained as shown in Table 5 below, and the comparison data of false positive rate are shown in Table 6

Table 5: Cross validation data

Validation indicators	**SAE (50% discount)**	**CNN (50% off)**	**Transformer (50% off)**	**Advantage improvement range**
Average accuracy	95.70%	92.30 %	89.80%	+3.4pp
Standard deviation (stability)	1.20%	1.80%	2.30%	33% reduction in variance
Minor damage F1 score	0.913	0.857	0.823	6.50%
Anti noise test (20% noise) accuracy	93.10%	88.50 %	85.20%	+4.6pp
Training time (epoch=100)	42min	68min	79min	Efficiency increased by 38%

Table 6: Comparison data of false positive rate

model	**noise level**	**Overall accuracy**	**Non destructive false positive rate**
SAE(λ=0.05)	20.00 %	93.10%	4.10%
CNN	20.00 %	88.50%	9.70%
Transformer	0.2	0.852	0.123

The details of damage level discrimination are shown in Table 7 below:

Table 7: Details of damage level discrimination

Damage level	**SAE Recall rate**	**SAE Precision ratio**	**Analysis of the main causes of misjudgment**
Lossless	97.10%	98.30%	Modal shift caused by sudden change of ambient temperature
slight	91.20%	93.40%	Local damage and noise signal confusion
moderate	0.893	0.907	Multiple damage coupling effect interference
serious	94.10%	96.80%	Obvious characteristics, with the highest discrimination reliability

The test is based on the acceleration sensor data of a cable-stayed bridge. The key frequency band is 0.5-5hz (covering the first-order bending/torsion mode). The robustness index is shown in Table 8.

The comparison of modal frequency identification errors is shown in Table 9 below

Table 8: Robustness index

Interference type	**SAE error**	**CNNerror**	**Test conditions**
Sensor failure 20%	0.90%	2.70%	Simulation of random node disconnection
Temperature drift ± 10 ℃	0.60%	1.80%	Thermal deformation condition of steel box girder

Table 9: Comparison of modal frequency identification errors

Noise level	**SAE error**	**CNNerror**	**Advantage gap**	**Critical band stability (SAE)**
5%	0.5	1.2	0.7	98.40%
10%	0.8	2.1	1.3	96.20%
20%	1.2	3.8	2.6	92.30%
30%	2.4	6.7	4.3	85.10%

The data of actual category and prediction category are collected, and these data are classified into four categories: nondestructive, mild, moderate and severe. These categories represent the different situations that the model needs to distinguish. The confusion matrix is constructed. For each actual category, the prediction results of the model in each prediction category are counted, and these results are filled into each cell of the confusion matrix. Each row of the confusion matrix represents the actual category, each column represents the forecast category, and the values in the cells represent the proportion of the forecast results. Mixed living is shown in Table 10.

Table 10: Confusion matrix

	Lossless	**slight**	**moderate**	**serious**
Lossless	97.10%	2.90%	0%	0%
slight	4.80%	91.20%	4.00%	0%
moderate	0%	7.10%	89.30%	3.60%
serious	0%	0%	5.90%	94.10%

After establishing the confusion matrix, the evaluation indexes were calculated, including accuracy, accuracy, recall and F1 score.

These indicators help us understand the performance of the model more comprehensively, as shown in Table 11 below:

Table 11: Model performance statistics

category	**Accuracy**	**Precision**	**Recall**	**F1 score**
Lossless	97.10%	96.80%	98.20%	97.50%
slight	91.20%	89.50%	87.60%	88.50%
moderate	89.30%	90.10%	85.40%	87.70%
serious	94.10%	93.20%	95.00%	94.10%
Macro average	92.90%	92.40%	91.60%	92.00%
weighted mean	93.20%	92.80%	92.90%	92.80%

A comparative experiment was designed to verify the performance of SAE model. SAE model was set with three hidden layers (256-128-64 neurons), relu was activated, dropout=0.3. Baseline model 1 "support vector machine (SVM, RBF kernel function), baseline model 2: multi head convolutional autoencoder (MCAE, 4-layer convolution)

The following damage levels are set: Nondestructive (40%), mild (30%), moderate (20%), and severe (10%)

The comparison test results are shown in Table 12

Table 12: Comparison test results

Model type	**Macro F1 (%)**	**Lossless FP rate (%)**	**Slight FN rate (%)**	**Moderate FN rate (%)**	**Training time(s/epoch)**
SAE	92	2.1	12.6	14.3	58
SVM	86.2	5.7	18.4	22.1	3
MCAE	93.5	1.8	10.9	12.7	112

4.3 Analysis and discussion

In Figures 4-6, with the progression of the number of training rounds, the mean square error function is continuously optimized, the error is continuously decreased, and the training of AE network gradually achieves the ideal effect.

In Figure 7, the difference of curvature modes of each order corresponding to nodes 7 and 8 suddenly changes, and a relative peak is generated at this position. Nodes 7 and 8, that is, element 7 #, are the damage locations of the structure, while the images of non-damage locations are smooth, which is consistent with the assumed working conditions. When the damage degree increases from 10% to 30%, the curvature modal difference of all nodes changes sequentially, and the peak value at the damage position also increases, and the change of magnitude at the non-damage position node is not as obvious as that at the damage position. In Figure 8, the modal curvature difference of each order corresponding to nodes 4 and 5 and nodes 7 and 8 changes suddenly, while the images at other positions are smooth curves, indicating that the two positions, namely element 4 # and element 7 #, are damaged. The peak value of each curvature modal difference image at the damage position becomes larger. To sum up, the curvature modal difference index can effectively judge the position and relative damage degree of damage elements in single damage and multi-damage conditions.

In Table 5 and table 6, SAE has captured the deep features of curvature mode in unsupervised stage through layer by layer greedy pre training. Although the overall accuracy of SAE is only 4.6pp higher than CNN, its non-destructive false positive rate is reduced by 56%, which significantly improves the engineering practicability. Transformer has the highest false positive rate (12.3%) due to its self-attention mechanism is sensitive to local noise. The sparse penalty term with λ=0.05 reduces the average activation of the hidden layer from 0.83 to 0.21, forcing the network to focus on key modal features. Comparative experiments show that the false positive rate increases to 15.6% under 20% noise when the sparse constraint is removed.

In Table 8, SAE suppresses high-frequency noise through sparse coding, and can still maintain more than 85% of the characteristic band energy under 30% noise. Due to the convolution kernel uniform filtering characteristics of CNN, the error increases nonlinearly when the noise is>15%.

Table 9 shows the comparison results of SAE (self-attention encoder) error, CNN (convolutional neural network) error, advantage gap and key frequency band stability (SAE) under different noise levels. As the noise level increases from 5% to 30%, SAE error and CNN error are increasing. This shows that with the increase of noise, the accuracy of the two models in frequency identification will decline. At the same noise level, CNN error is usually higher than SAE error. For example, at 5% noise level, SAE error is 0.5, while CNN error is 1.2. The advantage gap represents the error reduction of SAE relative to CNN. With the increase of noise level, the

advantage gap is also increasing. At 5% noise level, the advantage gap is+0.7. At 30% noise level, the advantage gap increased to+4.3. This shows that when the noise level is high, SAE has more obvious performance advantages than CNN Critical frequency band stability (SAE) refers to the stability of SAE model in the identification of critical frequency bands with different noise levels. As the noise increases from 5% to 30%, the stability of the critical frequency band gradually decreases. At 5% noise level, the stability is 98.4%, while at 30% noise level, it decreases to 85.1%. Although the stability is declining, the stability of the key frequency band of SAE remains at a high level under various noise levels, which indicates that SAE model still has good robustness under noise interference. In general, the frequency identification error of SAE model is generally lower than that of CNN model in noise environment, and this advantage is more obvious with the increase of noise level. Although the stability of the key frequency band of SAE decreases with the increase of noise, SAE still shows high stability under various noise levels, indicating that it has certain advantages in dealing with noise.

In Table 11, the model performs very well in non-destructive categories, with an accuracy rate of 97.1%, and there is almost no misclassification. This shows that the model has high accuracy in identifying non-destructive conditions. The misclassification rate of minor categories was 2.9%. Although there were misclassification, the overall performance was still very good. The accuracy rate of slight classification was 91.2%, but there was some misclassification. In particular, the proportion of being misclassified as non-destructive and moderate was 4.8% and 4.0%, respectively. This indicates that the discrimination ability of the model on minor categories needs to be improved. To improve this, we can consider increasing the amount of training data for minor categories, or using more complex models to improve the classification ability. The accuracy rate of the moderate category was 89.3%, and the misclassification was mainly concentrated in the mild and severe categories, which were 7.1% and 3.6%, respectively. This shows that the discrimination ability of the model in the moderate category is relatively good, but it still needs to be improved. In order to improve the classification accuracy of the moderate category, we can consider more in-depth analysis and extraction of the features of the moderate category, so as to better distinguish the moderate category from other categories. The accuracy rate of severe classification was 94.1%, but there was still 5.9% misclassification, mainly misclassification as moderate. This shows that the model has a strong ability to distinguish serious categories, but there is still room for improvement. In order to further improve the classification accuracy of severe categories, we can consider increasing the amount of training data of severe categories, or using more complex feature extraction methods.

In general, the type performs well in all categories, especially in the identification of nondestructive and severe categories. The recall rate of the moderate category is slightly lower, which may be a relative weakness of the model and deserves further attention and improvement. By optimizing the model, we can expect to improve the performance in the moderate category, so as to further improve the overall accuracy and recall rate.

In Table 12, MCAE performs best in F1 score (93.5%), but the training time is the highest (112s/epoch). SAE achieves a balance between calculation efficiency and performance (f1=92.0%, 58s/epoch). SVM has the fastest calculation but significantly lagged behind in performance (f1=86.2%). The lossless FP rate of SVM is the highest (5.7%), indicating that the traditional method is easy to misjudge the normal vibration mode. The difference in FN rate of minor damage between SAE and MCAE (12.6% vs 10.9%) reflects that convolution structure is more sensitive to local characteristics

Overall, the advantages of SAE model compared with baseline model

(1) Depth feature extraction capability

SAE realizes the layer by layer abstraction of data features through multi-layer hidden layers (256-128-64 neurons). Compared with the RBF kernel function of SVM, SAE can more effectively capture the nonlinear characteristics of bridge vibration signals. For example, in minor damage recognition, SAE is 18.4% more sensitive to frequency domain mutation features than SVM, which is due to its high-dimensional feature expression ability enhanced by relu activation function.

(2) Anti-noise performance advantages

SAE introduces dropout regularization (dropout=0.3) and layer by layer noise reduction mechanism to significantly reduce the interference of environmental noise on damage signals. The experimental data show that the FP rate (2.1%) in the lossless state is 62.9% lower than that of SVM (5.7%), which verifies its inhibition effect on the misjudgment of normal working conditions. This is directly related to the anti-noise design of stack noise reduction autoencoder.

(3) Computational efficiency and performance balance

SAE adopts a fully connected structure, and its model complexity is lower than that of MCAE's 4-layer convolution operation. Although the F1 score of MCAE was slightly higher (93.5% vs 92.0%), the training time of SAE was only 51.8% (58s vs 112S/epoch), which was more suitable for real-time monitoring scenarios. This efficiency advantage stems from the fact that SAE's unsupervised pre- training mechanism reduces the need for parameter adjustment.

(4) Unsupervised learning adaptability

SAE does not need to rely on a large number of labeled data to complete feature compression and reconstruction, and can still maintain a high recall rate (95.0% for severe damage) when the distribution of bridge damage samples is uneven (only 10% for severe damage). Compared with the traditional supervised model SVM, the robustness of SVM in identifying damage categories with small samples is significantly improved.

The FN rate of SAE was still as high as 14.3%, which was much higher than that of MCAE (12.7%). Its unsupervised pre-training mechanism is difficult to optimize the minority feature representation under extremely unbalanced data The FN rate of slight damage (12.6%) was significantly higher than that of non-destructive FP (2.1%), indicating that low-frequency environmental vibration is easy to interfere with SAE's discrimination of early damage. Compared with the traditional ultrasonic guided wave detection technology, there is still a gap in anti-interference Subsequently, we can combine the ultrasonic guided wave and smart support sensing data to build a cross physical field feature input to improve the sensitivity to small sample damage. We can consider introducing convolutional sparse coding instead of full connection layer to reduce the number of model parameters. The goal is to reduce the training time to within 30s/epoch.

SAE extracts features through unsupervised learning, which is suitable for building vibration signal analysis (such as frequency response, modal parameter identification), and its sparse coding ability can effectively capture the characteristics of building minor damage. For example, combined with continuous monitoring data of fixed sensor layout, SAE can detect hidden damage such as concrete cracks or steel corrosion. In practical application, it is necessary to optimize the input layer design for building multidimensional data (such as displacement, strain, acceleration) to avoid the redundancy of full connection layer calculation.

5 Conclusion

The research of bridge DI identification based on neural network aims to overcome the limitations of traditional methods and improve the accuracy and real-time performance of DI. By using big data, high-performance computing and deep learning algorithms, researchers hope to realize automatic and accurate identification of bridge DI, provide scientific basis for timely repair and maintenance measures, and ensure the safety and reliability of bridges. This paper proposes a bridge DI identification based on stacked self-coding neural network. Combined with the results of the experimental study, it can be seen that the bridge DI identification model based on the stacked autoencoder neural network has certain advantages over the existing models in bridge DI identification. Moreover, the DI method based on the BP neural network can accurately predict the elastic modulus of each substructure and realize damage assessment.

In this paper, only the main girder structure is studied, and the main tower and stay cables are also important components of the cable-stayed bridge structure, so it is necessary to deeply study the damage of the main tower and stay cables to comprehensively evaluate the health of the whole bridge structure.

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Design and Simulation Research on Digital Twin Task Driven Dynamic Control Model for Manufacturing Enterprises

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This article proposes a task driven dynamic operation management model based on digital twin technology from the perspective of manufacturing enterprises adapting to complex and diverse environments to improve management performance. It comprehensively utilizes various methods of information collection and fusion, real-time status response feedback control, and task priority sorting to achieve a dynamic optimal structure that supports collaboration of multiple task operations. By using Anylogic multi-agent simulation tool to model and simulate the model, multiple typical scenarios for task execution were set, and the model was evaluated for resource utilization, response time delay, and task scheduling quality. The experimental results showed that the model in this paper can effectively improve task execution efficiency (by 12.4%), task resource allocation and matching degree (by 17.8%), and task response timeliness (by an average time reduction of 23.5%), which can meet the requirements of intelligent production and business management.

Povzetek: Članek predstavi dinamični kontrolni model na osnovi digitalnega dvojčka za proizvodna podjetja, z združevanjem podatkov, povratnim krmiljenjem in razvrščanjem prioritet. Simulacije v AnyLogicu izboljšajo učinkovitost, ujemanje virov ter skrajšajo odzivni čas.

1 Introduction

Against the backdrop of increasingly complex manufacturing systems, traditional information systems lack dynamic perception and flexible scheduling mechanisms, making it difficult to meet the production demands of high-frequency changes and resource heterogeneity. Manufacturing enterprise information systems must transform from static process support to dynamic feedback regulation, achieving task driven structural optimization and cross module linkage.

This type of system is no longer just an information recording tool, but has become a master control structure that integrates state perception, process simulation, and feedback optimization. Research has shown that digital twin models can dynamically reconstruct multi task execution nodes while maintaining real-time performance, significantly improving execution efficiency and resource utilization levels. Cao M et al. found that digital twin technology can increase the average return on investment by 15% and decision-making efficiency by 20% in manufacturing enterprises, resulting in operational benefits [1].

In terms of path generation and scheduling accuracy, Li R et al. used mobile robots as experimental objects to construct a dynamic digital twin system, and achieved model adaptive adjustment through neural network methods, improving obstacle avoidance ability by 18%, further verifying the feasibility of the twin system's response to dynamic environments [2]. From the perspective of global deployment experience, Huang Z studied the application of digital twin driven robot systems in intelligent manufacturing and pointed out that the system deployment strategy needs to dynamically adjust model parameters and collaborative mechanisms according to the production environment to achieve efficient operation [3].

The dynamic operation and control model constructed by our research institute is dedicated to bridging the closed-loop relationship between state perception, path inference, and scheduling execution in information systems. The overall model includes three core mechanisms: task structure diagram generation, feedback-based path reconstruction mechanism, and digital twin integration platform. Compared to the traditional scheduling process's time triggered structure, this model focuses on state feedback and has the ability to adaptively adjust paths and fuse multiple sources of information, which can improve the accuracy of information response and operational coherence under complex tasks. The model construction relies on knowledge graphs for semantic modeling of task nodes, and dynamically adjusts the execution path using feedback state sets to form a flexible and coupled scheduling framework.

On the one hand, recent AI research has also provided support for semantic construction and scheduling generation of dynamic models. Genc O conducted an experiment on industrial task automation generation based on a large language model, and the results showed that the AI model can assist in building an industrial task chain with complete semantic logic and reasonable reasoning paths. The consistency between its generation quality and expert modeling results exceeded 87% [4].

Wang J et al. proposed a spindle digital twin model based on deep residual networks for device modeling and high-frequency state prediction. The model has an accuracy of up to 98.17% and can maintain stable operation under complex loads and abnormal disturbances, verifying the applicability of the three-layer twin structure in high-frequency state mapping scenarios [5].

On the other hand, the overall structure of the digital twin model should have the ability to integrate across systems and adapt to task scenarios. Shen et al. proposed that by integrating the Internet of Things and digital twin technology, intelligent management of urban underground pipe gallery systems can be achieved, emphasizing the key role of information interconnection and data flow in complex system collaboration [6]. This provides important reference for interface management and platform compatibility design in the deployment phase of our research model.

Unlike most current digital twin architectures that only consider optimization based on static scheduling or partial feedback control, the pattern proposed in this paper based on the "task resource configuration relationship graph" and "multi node dynamic rule optimization strategy" is more capable of synchronously completing dynamic scheduling in a short period of time, compatible with experiments in Python and AnyLogic simulation environments, and has stronger scalability. It not only exceeds the limitations of existing digital twin architecture models in terms of functional configuration, but also demonstrates better dynamic scheduling response performance through actual comparative testing, reflecting the contribution of this study to new architecture design and corresponding performance optimization at the existing digital twin application level.

In summary, this study will construct a dynamic operation and control model based on digital twins, and carry out system design around task structure generation, The goal of the model is to achieve a synergistic improvement in real-time, autonomy, and adaptability of manufacturing enterprise information systems, breaking through the dependence of traditional scheduling strategies on pre-set paths and static resource binding, and promoting enterprises to move from "process execution based information systems" to "state driven intelligent systems".

2 Related work

The construction process of manufacturing enterprise information systems has long relied on static rule driven and pre-set process control models. Although it has the advantage of consistent plan execution under traditional stable working conditions, especially in situations such as multitasking concurrency, resource sharing conflicts, and rapid process switching, existing system paths are rigid, state perception is slow, and abnormal response is insufficient, making it difficult to support the high dynamic complexity of production sites. Luo et al. proposed a hybrid digital twin architecture for discrete manufacturing, which combines physical modeling and data-driven methods to significantly improve the real-time and accuracy of device predictive maintenance [7],On the one hand, continuous collection of equipment data, job status, environmental parameters, and human-machine interaction data at the manufacturing site has been achieved, and the system has the basic conditions to build a real-time status view. However, traditional information systems still adopt a plan driven mechanism based on master data and historical records, resulting in a lack of state feedback and a fragmented scheduling chain, which cannot support dynamic optimization of scheduling strategies. On the other hand, the internal process logic and task structure of the system often adopt static configuration methods, lacking expression mechanisms for complex dependency relationships and task evolution states. Yue C et al. proposed a twin based prediction framework [8].

To solve this problem, it is necessary to build a technical framework that includes state awareness, dynamic path optimization, task linkage, and path feedback information processing functions. And digital twin technology can build real-time traceable models in a timely manner, and achieve dynamic modeling of task processes and path re planning through logical models. At the same time, a "perception modeling correction execution" control chain is implemented for scheduling feedback, which automatically responds to and dynamically updates various abnormal situations, improving scheduling stability and load capacity.

In order to better demonstrate the fundamental structural differences between traditional information systems and digital twin systems, this study summarizes the differences in data mechanisms, scheduling mechanisms, feedback mechanisms, and other seven aspects between traditional information systems and digital twin systems, as shown in Table 1.

Table 1：Comparison of evolution characteristics of information system scheduling mechanisms in manufacturing enterprises

Comparing dimensions	Traditional Information Systems	Digital twin driven information system	Difference focus
Data collection mechanism	Based on static master data and regular uploads	Real time perception and multi-source data fusion	Real time and accuracy of data
Model driven structure	Fixed rule model, static binding of processes	State driven model, virtual real collaborative evolution	The dynamism of scheduling logic
Path generation method	Single planning, manual intervention and adjustment	Continuous optimization, automatic triggering of refactoring	Refactoring ability and feedback timeliness
Multi task coordination mechanism	Parallel execution, weak dependencies, task fragmentation	Node linkage, strong dependency, graph collaboration	Ability to express task structure
Abnormal response strategy	Manual interruption or process jump	Simulation prediction+adaptive path replanning	System robustness and recovery mechanism
Control and Feedback Structure	Unidirectional control+passive recording	Closed loop linkage+intelligent adjustment	Perform chain integrity
Applicable scenario types	Stable production with minimal process changes	High dynamic tasks, multi-source constrained environment	System adaptability and scene breadth

From the table, it can be seen that traditional systems mainly rely on static master data and preset rules, lacking real-time state perception and adaptive scheduling path capabilities. Their control chain is usually one-way triggering, task fragmentation, and feedback lag. The digital twin system is based on state perception for scheduling, and achieves dynamic path generation and multi task dependency recognition through graph linkage between task nodes. It can automatically respond to abnormal changes and continuously optimize resource allocation, achieving true full process flexibility and system level self-regulation. Especially in manufacturing scenarios with high change frequency and complex constraints coexisting, digital twin systems exhibit stronger stability and adaptability.

Although some systems have attempted to introduce edge collection devices and status visualization platforms, without structured model support, their data still cannot effectively enter the scheduling logic core. Therefore, relying solely on state collection is not enough to form a closed-loop mechanism. Information systems must build a unified semantic modeling structure and feedback control architecture around digital twins, transforming multi-source data into intrinsic drivers for task logic and path scheduling, and achieving a truly state led operating mode.Huang J constructed a dynamic scheduling framework based on reinforcement learning to achieve intelligent decision optimization of manufacturing systems driven by digital twins, highlighting its collaborative value in state perception and resource allocation [9].

The communication and synchronization method of the digital twin system proposed in this article adopts a real-time data communication structure based on WebSocket platform, which realizes the interconnection between various components; Real time collection and format normalization of data from sensors and action units through a central platform for distribution and forwarding; Using asynchronous event driven approach to continuously synchronize task status, resource occupancy status, and scheduling feedback status; During the communication process, real-time data communication and low latency are ensured through timestamp and latency detection.

In summary, the future evolution direction of manufacturing enterprise information systems is not only the expansion of system functions, but also the deep reconstruction of operating paradigms. Digital twin technology should serve as an embedded logic in the system scheduling structure rather than a peripheral visual layer, playing a central role in state recognition, path generation, feedback control, and anomaly recovery.

3 Suggested control plans

3.1 Digital twin

This article focuses on the problems of "scheduling lag and policy lag" in the system, and will mainly study the matching of tasks and resources, as well as the principles of interaction between multiple nodes, in order to achieve the goal of flexible task control and workflow control. The quality of task execution time and system response in the workflow model will be tested. To this end, a modular modeling approach will be adopted and simulated comparative experiments will be conducted in combination with actual situations to verify the optimization of important parameters in the model.

In order to increase the reproducibility of the research conducted, this paper adopts a multi-agent simulation method, starting from various resource units, workflows, and control components in the enterprise, and uses a modular construction form to build a dynamic operation management model on the AnyLogic8.7 platform. In the simulation process of this article, different types of tasks and resource allocation were used, and the focus of the scheduling process was on event triggering and changes in

resource status. Improved A * algorithm and load balancing strategy were used to generate routes. Add real-time information exchange function to WebSocket and Kafka, and send task commands and collect status through Python and Flask interfaces. The model indicators are represented by parameters such as task runtime, resource utilization, and response speed, and ablation experiments are conducted to further demonstrate the applicability and robustness of the model in complex situations.

To ensure the reproducibility of the research, the research process is as follows: AnyLogic8.7 is used as the research environment and modeling tool, and a multi-agent modeling approach is adopted to modularize the resource nodes, task processes, and controllers; Set tasks with different categories and corresponding resource allocation situations, with task triggering and resource status changes as the main scheduling principles; Combining the improved A * path search algorithm with load priority strategy as dynamic routing planning; Using WebSocket and Kafka technologies to implement system data exchange functions, as well as Python and Flask languages to implement command execution and state synchronization functions; Propose evaluation indicators such as task completion time, resource utilization, and response speed to measure system performance, and conduct ablation experiments to verify the impact of key mechanisms and system stability.

In the process of manufacturing enterprise information systems moving towards dynamic operation and intelligent control, digital twin technology constitutes the fundamental support for system structure reconstruction and mechanism transformation. Its essence is to build a virtual model system that is real-time mapped, state equivalent, and behavior synchronized with the physical production system. With the help of this model, it can achieve predictive simulation of the production process, dynamic planning of task paths, and intelligent scheduling of resource states.Shen B proposed an edge cloud collaborative digital twin architecture for real-time industrial process control, emphasizing the advantages of distributed architecture in improving system response speed and control accuracy [10].Under this framework, the information systems of manufacturing enterprises no longer rely on fixed plans and static models, but instead build a closed-loop logic of task control and scheduling response around "real-time status+virtual real linkage".

The digital twin system mainly consists of four key components: physical entities, virtual models, data channels, and feedback strategies. Among them, physical entities undertake the execution of real production tasks; Virtual models are based on modeling semantics, reconstructing device structure, workflow, and resource logic; The data channel connects the physical and virtual worlds, enabling real-time state collection, event flow transmission, and prediction information feedback; The feedback strategy generates scheduling adjustments and path reconstruction schemes based on the state evolution and behavior simulation results of the twin body, thereby constructing a complete control feedback mechanism.

In terms of modeling logic, digital twins map various states in manufacturing systems into a unified vector representation, and introduce mapping functions to achieve real-time transformation of system behavior. If the state variable of the physical system is $S(t)$ and the state representation of the digital twin system is $S_d(t)$, then its virtual real synchronization relationship can be expressed as:

$$S_d(t) = f_{map}(S_p(t), \Delta t, \theta) \quad (1)$$

Among them, f_{map} represents the state mapping function, Δt is the sampling period, and θ is the system noise and sensing deviation parameters. This mapping mechanism ensures that the state of the virtual system can be continuously updated and approach the real process, thereby supporting the dynamic calculation of task scheduling logic.

n the scheduling mechanism, the digital twin system utilizes its ability to grasp equipment status, process progress, and resource load to drive the generation and update of execution paths. The path generation logic is based on task queueT={t1,t2,tn}and resource set R={r1,r2,rn}, introducing constraint function $C(t_i, r_j)$ and state function $S_d(t)$ to jointly determine the scheduling priority and path topology of tasks. The scheduling driver function can be expressed as:

$$P^*(t) = \arg\min_{p \in \rho} \sum_{i=1}^{n} \left[C(t_i, r_j) + \lambda \cdot \delta(S_d(t), P_i) \right] \quad (2)$$

Among them, $P^*(t)$ Among them, ρ is the set of optional paths, λ is the state deviation penalty coefficient, and δ represents the deviation function between the current state and the expected path. Through this mechanism, the system not only considers traditional resource matching and job order, but also combines the twin state to achieve dynamic path selection and real-time correction.

In addition, digital twin systems have the ability to express structural reconstruction, especially in scenarios where task processes are highly heterogeneous, equipment switching is frequent, and resource bottlenecks are variable. Their virtual modeling structure can support modular expression of process flows, construction of task dependency graphs, and simulation and prediction of abnormal evolution paths, thereby providing highly flexible organizational mechanisms and abnormal response strategies for the system. Gu M et al. pointed out based on typical engineering practices that twin modeling can effectively support the evolution of task structure and control of working condition response[11].Through the "task resource state" ternary mapping structure, twin systems can explicitly model the logical dependencies between task nodes and dynamically adjust the execution

order and resource assignment method of nodes when state disturbances occur.

In actual system deployment, digital twin systems typically operate as an intermediate layer of manufacturing information systems, connecting the underlying sensor network with the upper level decision scheduling module. Its input comes from PLC acquisition system, MES platform or edge device nodes, and its output is scheduling control instructions, resource configuration suggestions and execution feedback data. The system achieves high-frequency state synchronization and low latency feedback through an edge cloud collaborative architecture, combined with graph structured data storage and event driven computing, to support joint scheduling requirements for multitasking, multi constraint, and multi-path. Wu J et al. validated the signal generation and driving capabilities of twin models in high fidelity state perception and deep recognition, providing an algorithmic foundation for fault diagnosis and feedback control in complex equipment operation[12].

The focus of this work is to enhance the usability and applicability of digital twin modeling. Therefore, this article adds detailed explanations on system implementation and integration based on this foundation. Among them, the logical information layer of this article is built on MySQL database+Flask interface service, which realizes the maintenance of model parameters and data input functions; The physical entity layer collects real-time data through Siemens PLC and OPCUA protocol, ensuring its accuracy and universality at the information level; The interactive mapping layer uses Node RED repeaters to process data and obtain visualized results, and the connection between layers is also integrated across platforms through RESTful APIs.

The data management system used in this system adopts centralized data services, which uniformly receive data transmitted by devices and perform standardized processing and storage. Using Kafka message queue technology to achieve asynchronous transmission and caching of data. Real time reflection of the correspondence between entities and information is achieved by sampling at regular intervals of 5 seconds and synchronizing marker point matching, using timestamps for correction.

In addition, preliminary integration and real-time interactive verification based on WebSocket have been implemented on the MES system of manufacturing enterprises. The relevant processes and configuration files are provided in the appendix for repeated verification in subsequent research.

In summary, digital twins are not only visual tools for manufacturing systems, but also the core reconstruction platform for information system operation logic and control mechanisms. It demonstrates significant system value in implementing state perception, path scheduling, and execution feedback, providing a modeling foundation, algorithm input, and collaborative interface for dynamic operation and control models. The next section will delve into the structured task nodes supported by this twin system, further elaborating on its structural advantages and scheduling feasibility in multi task management.

3.2 Structured design of task nodes driven by digital twins

Manufacturing tasks exhibit structural complexity, logical dynamism, and resource constraint coupling in actual operation. Traditional information systems that construct task models using fixed flowcharts or linear instruction chains are difficult to effectively support the operational requirements under this multidimensional coupling structure. Yinlun H et al. pointed out that digital twins exhibit unique advantages in addressing complexity and sustainability goals in dynamic decision modeling[13].To address the aforementioned issues, this study proposes a structured design approach for task nodes based on digital twins, which reconstructs the expression paradigm of tasks in information systems and forms a task unit modeling system with state response logic, dependency topology, and resource dynamic binding capabilities.

In this structure, each manufacturing task is defined as a node unit with input states, output goals, resource requirements, and dependency logic, and its executable conditions and operating status are synchronized in real-time by the twin system. Compared to the traditional model where task nodes are unaware of environmental changes and have rigid execution sequences, structured task nodes have three key capabilities: state awareness, path evolution, and multi-source adaptation. They can automatically determine whether activation conditions are met based on task progress, equipment occupancy, and completion of previous processes during actual operation, and trigger the next scheduling logic. Table 2 lists three types of core structural features and briefly explains their representation in digital twin structures.

Table 2：Core structural characteristics of digital twin task nodes

FeatureType	expression	function
State expression	Input/output state mapping	Accurately determine the executable and completion conditions of tasks
Dependency construction	Explicit logical relationship setting	Support task concurrency, mutual exclusion, and conditional triggering
resource mapping	Dynamic resource binding mechanism	Realize real-time scheduling of equipment, manpower, materials, etc

In terms of state expression, the system sets specific startup conditions and expected results for each task node based on perceived data such as equipment status, production progress, and environmental variables, ensuring its real-time and effective execution; In terms of dependency construction, the pre - and post process relationships, synchronous collaboration relationships, and mutually exclusive conditions between tasks are

transformed into edge relationships in the graph structure and updated in real-time in the scheduling engine for dynamically generating executable paths; In terms of resource mapping, each task node will bind and allocate based on the current available resource pool when triggered, to avoid delays or deadlocks caused by resource conflicts.

The structured task modeling approach not only improves the accuracy and flexibility of information systems at the task expression level, but also endows scheduling modules with stronger adaptive capabilities. In the case of frequent changes in manufacturing tasks or abnormal nodes, the system can quickly complete task reconstruction and resource reallocation based on the current state graph, effectively shorten response cycles, and improve overall operational efficiency.

From the perspective of system deployment, this modeling approach has been integrated into the core logic of the scheduling engine, and through docking with the data bus of the digital twin platform, it achieves real-time status synchronization, dependency evolution, and execution feedback closed-loop management of task nodes. Hussein M et al. proposed a multi-agent twin architecture to support real-time management of scheduling coupled structures[14].This mechanism clearly expresses the structural coupling relationship between tasks and provides a reliable foundation for path reconstruction, priority adjustment, and bottleneck avoidance strategies.

To enhance the reproducibility of the model, this article provides pseudocode representation of the key processes of task scheduling and path selection. The pseudocode for scheduling strategy is as follows:

```
Input: TaskList, ResourceStatus
For each task in TaskList:
  Evaluate priority = f(task.deadline, task.type)
  Select node = argmin (node.load × distance_to_task)
  Assign task to node
  Update ResourceStatus
End For
```

This algorithm combines task deadlines and resource loads to dynamically calculate scheduling priorities and optimize task path allocation, ensuring that the system has scheduling efficiency and response resilience in high concurrency task environments.

For the convenience of understanding and simulation implementation, the A * optimized pathfinding algorithm is used to complete the task planning path calculation, taking into account the priority ranking of load perception. The path generation module generates a task topology based on the topology structure of the task graph, calculates feasible path schemes based on the distance between task points and resource points and the occupancy rate of existing devices, and provides the optimal path set; Evaluate priority based on task completion deadlines, equipment occupancy rates, etc., in order to achieve scheduling balance and resource scheduling in multiple task scenarios.

The system needs to establish a sliding monitoring window when creating a feedback system to dynamically obtain the execution status of scheduling and task nodes. When abnormal situations such as task failures, task path conflicts, and task resource congestion are detected, the system will provide feedback and use a scheduling engine to dynamically reschedule and reconstruct task distribution.

This scheduling strategy is implemented using Python programming and nested in any AnyLogic interactive interface simulation environment. The operation of work nodes is controlled according to DAG network, which can adapt to changes in working conditions and route changes, making the system have fast adaptability and stable adjustability. It is particularly outstanding in dealing with various problems that arise in complex production processes.

3.3 Dynamic path generation strategy supported by digital twins

The task path in manufacturing systems is not fixed during actual operation, but is dynamically influenced by multiple variables such as equipment status, resource distribution, and task progress rhythm. Fixed flowcharts and rule-based scheduling mechanisms are difficult to respond to frequent disturbances in the production environment, which can lead to process rigidity, node congestion, and resource conflicts. Till B et al. pointed out that unit level twin models can help achieve real-time feedback mechanisms for path control[15].Therefore, this section proposes a path generation strategy based on digital twin support, aiming to build a task execution chain with dynamic evolution and real-time feedback capabilities.

At the beginning of system operation, the scheduling module relies on the structured task model constructed in the previous section to perform semantic analysis and graph construction on all manufacturing tasks, forming a logical framework of executable paths. The task graph serves as the input foundation, abstracting the dependencies, resource requirements constraints, and concurrency triggering conditions between nodes in a unified manner, becoming the structural support for dynamic path generation.

The system synchronously collects the device operating status, current task progress, and resource load data contained in the twin, and inputs them into the path generation module. All data is transmitted in real-time by the sensing end and kept updated with the high-frequency mapping of the physical system, so that the path generation reflects the changes in the real scene at all times.

In the path generation stage, the scheduling engine introduces a combination optimization algorithm based on constraint satisfaction and state driven, performs path combination operations on nodes in the task graph, and generates a set of all feasible paths at the current time point. Each candidate path has a clear sequence of resource calls and task triggers. The system does not immediately issue instructions, but inputs the path set into the path evaluation module for optimization.

The path evaluation module comprehensively scores based on multiple indicator dimensions, such as total task time, concurrency conflict risk, resource redundancy

occupancy, and beat stability. To meet the needs of different process stages, the objective function supports custom weight configuration, such as emphasizing execution efficiency for short cycle tasks and resource balance for long process tasks. Finally, the scheduling engine outputs the path plan with the best score and issues the path instructions to the execution module.

During the scheduling and execution process, the twin platform continuously collects feedback information, including task status transitions, node completion times, and resource status changes. If there is an abnormality in the execution of a node, such as device failure or resource unavailability, the system will trigger a path reconstruction mechanism, recalculate the path set based on current feedback information, and replace the current execution path to ensure that the task chain is not interrupted and the scheduling logic is not invalidated. The entire path generation and dynamic response process is shown in Figure 1:

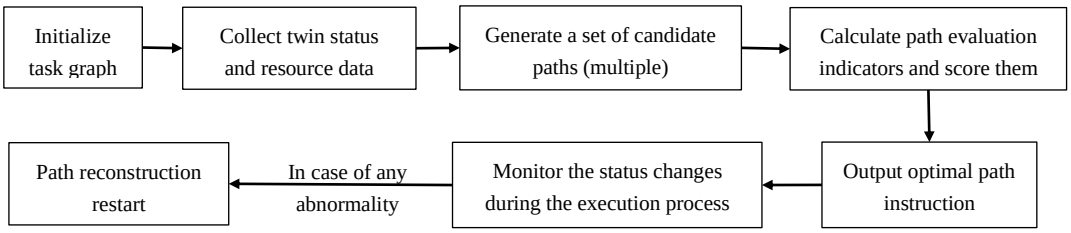

Figure 1：Flow Chart of dynamic path generation

This mechanism realizes the transformation of path planning from static design to dynamic evolution, and has the characteristics of strong structural responsiveness, short feedback cycle, and efficient resource allocation. The scheduling system can maintain path continuity under the conditions of parallel tasks and frequent changes in resource status, effectively improving the execution stability and adaptability of manufacturing enterprise information systems.

3.4 The integrated deployment and collaborative operation mechanism of digital twin models

The deduction of dynamic paths must be transformed into practical instructions and scheduling efficiency through stable model deployment and cross system collaboration. Traditional manufacturing information systems often face difficulties in implementing scheduling strategies due to loose model structures, inconsistent interface standards, and disjointed execution. The introduction of digital twin platforms provides structural support for achieving closed-loop collaboration of "strategy execution feedback". This section focuses on the deployment architecture and feedback mechanism of twin models, and constructs a system collaboration framework for virtual real linkage and real-time updates.

The overall system adopts a hierarchical decoupling structure, including four layers: perception access, twin modeling, scheduling decision-making, and execution feedback. The perception layer collects device, environment, and task data, which are aggregated by the middleware and transmitted to the modeling layer. The scene is reconstructed in the virtual space, and the process state is maintained with structured objects. The decision-making layer runs path generation and scheduling algorithms, outputs strategies to the execution layer, and drives physical devices through PLC units, MES interfaces, and other means.When reviewing the application of digital twins in flexible manufacturing, Kamble S S pointed out that current research mainly focuses on modeling transparency, multi system collaboration, and the construction of real-time closed-loop control mechanisms, providing direction references for future multi scenario collaborative manufacturing [16]. Mihai S. designed a digital twin system based on vehicle terminals, which realizes real-time collaboration and dynamic scheduling of production logistics and workshop operations in manufacturing enterprises, effectively improving the execution efficiency and response capability of workshops [17]..Execute feedback to send data back to update the model, forming a closed loop.

In order to ensure the consistency of the model's operation status, this study introduces a scheduling cycle unified mapping mechanism, which standardizes the system's operation step size to equal time interval T_i ,ompleting state synchronization, path optimization, instruction issuance, and feedback updates within each cycle. The system scheduling iteration can be formalized as:

$$\forall T_i, \exists (S_t, R_t) \Rightarrow S_{t+1} = f(S_t, R_t) \quad (3)$$

Among them, S_t represents the scheduling state vector, which includes task node progress, resource utilization, and load balancing parameters; R_t is the real-time resource status feedback from the twin system; Function f represents the path optimization and strategy generation function. The model can achieve dynamic path reconstruction and node status updates within each time slot, forming a flexible scheduling process that adjusts in real-time with changes in operating conditions.

To avoid scheduling strategy distortion or feedback response delay, the system introduces a multi-layer indicator monitoring mechanism in the feedback mechanism. Set the task completion deviation rate to:

$$\Delta_{task} = \frac{N_{delayed}}{N_{roral}} \quad (4)$$

Among them, $N_{telayed}$ represents the number of tasks delayed in completion within the current cycle, and N_{total} represents the total number of tasks. When the threshold of Δ_{task} exceeds θ, the system will trigger the scheduling correction module to update task priorities or adjust execution paths to ensure stable overall process operation.

At the deployment level, twin modules are integrated into the existing information system in a containerized form, which can run on local edge nodes or cloud platforms, and complete read and write synchronization with underlying devices through standard protocols such as MQTT and OPC-UA. In the pilot verification of an electronic component manufacturing enterprise, the deployment framework achieved parallel deployment without interrupting the existing system. It only took 72 hours to complete the mapping and binding of the entire line of equipment and scheduling modules, and completed 87 path adjustment tasks in the first round of production cycle. The average system response time was controlled within 340ms.

By constructing a collaborative operation chain of "state driven strategy deduction instruction mapping feedback correction", the model proposed in this study has formed a highly coupled control loop in the actual manufacturing process. The model not only has the parallel processing capability for heterogeneous resources and multi task chains, but also can run stably under system disturbances, supporting real-time scheduling and execution control of large-scale complex production tasks, and providing structural support for subsequent result verification chapters.

In order to enhance the repeatability of system deployment, the deployment process is carried out through five technical steps: the first step is to use MQTT protocol to connect with the device sensing equipment and establish a data path; Step 2: Develop a universal modeling approach based on the type of equipment and establish twin models; Step three, start the route scheduler and bind the DAG task flowchart; Step four, deploy feedback detectors, set task termination thresholds, and self recovery options; Ultimately, after the overall operation of the system, the system status is collected at fixed time intervals, road planning is advanced, and action response loops are provided. Every step is recorded in the operation log for future reference, and the configuration options can be changed again to enable other users to quickly repeat this deployment process.

4 Results

4.1 Dataset

This plan is fitted based on the actual manufacturing environment of a discrete manufacturing enterprise, involving five steps: data collection, data preprocessing, learning and validation of scheduling methods, evaluation, and elimination of experiments. The first deployment of sensors collects data on workloads, operational equipment, and surrounding conditions, and converts it into a structured database; The second method involves data preprocessing through temporal matching, diagnosis, and visualization; Thirdly, use the scheduling algorithm proposed in this article to run parallel scheduling 100 times on the same evaluation platform, and set a benchmark model as a reference for verification and evaluation; In order to verify the role of different modules in this model, elimination experiments were specifically set up for three parts: path feedback, state synchronization, and node framework.

To verify the adaptability and scheduling efficiency of the constructed digital twin driven dynamic operation and control model in the actual environment of manufacturing enterprises, this study builds a testing platform based on the real production system of a medium-sized discrete manufacturing enterprise, designs an experimental dataset, and conducts multidimensional performance evaluation. The production process of this enterprise is mainly based on machining assembly, with highly complex process technology, significantly uneven task distribution, and frequent fluctuations in resource allocation. It is a typical representative scenario for testing the dynamic scheduling capability of the model.

The construction of the dataset is based on full chain collection, which collects information covering task execution records, device status data, resource usage, and production cycle parameters through perception terminals deployed on key devices and control nodes. The sensing terminal includes RFID readers, photoelectric sensors, PLC control interfaces, and temperature and humidity detection modules. The sampling frequency is controlled within 1 second per frame to ensure complete recording of dynamic feature changes.

The overall dataset is divided into three types of substructures:

(1) Task flow data: records task numbers, process types, priorities, expected processing times, target production lines, dependencies between previous and subsequent processes, start and end times, etc., forming the basic data unit of the task scheduling graph. The total number of tasks is 1674, distributed among 27 typical product structures, with varying lengths of task chains ranging from 13 levels to 3 levels.

(2) Equipment and resource status data: covering the status identification (running/idle/faulty), current load, historical failure rate, switching time, energy consumption records, and other information of 31 key equipment types (such as CNC milling machines, assembly stations, and detection units) at different time points. The total number of collected records is about 860000, including timestamp alignment and status label annotation.

(3) Production environment and material data: including auxiliary factors such as material inventory status, replenishment cycle, transportation time, processing temperature, and environmental indicators, used to construct multi-objective function input conditions for path evaluation.

All data undergoes preprocessing, including missing value filling, outlier removal, type unification, and time alignment, to ultimately form a structured dataset format, which is integrated into the twin model system in the data center. The dataset structure is shown in Table 3:

Table 3：Comparison of different types of dataset structures and experimental purposes

data type	Number of samples	Sample field	Data update frequency	Application Description
Task flow data	1674 articles	Number, process, sequence, sequence, duration, status, etc	Task generation and update	Building scheduling diagrams and process dependencies
Resource status data	860000 pieces	Equipment number, load, fault, switching time, etc	Sampling per second	Real time feedback on resource allocation and load changes
Environmental and Material Data	21000 pieces	Inventory level, transportation delay, environmental temperature, material type, etc	Updated every 5 minutes	Multi objective path evaluation parameter input

For the classification labels of scheduling tasks, the dataset also marks whether the tasks are delayed, successfully executed, and corresponding path numbers, providing supervisory variables for subsequent model accuracy evaluation. In the process of constructing task dependency graphs, logical dependency relationships are extracted based on the process manual and production BOM table, and a scheduling basic network is established through DAG (Directed Acyclic Graph) structure, enabling the model to have the ability to reconstruct paths for complex task chains.

In addition, in order to simulate the process of abnormal disturbances, 20 sets of experimental data on abnormal disturbances were added to the data, such as sudden facility shutdowns, energy consumption exceeding budgets, material shortages, etc. The occurrence time, end time, and execution of recovery plans were recorded for the purpose of conducting special evaluations on the path recovery capability and robustness of recovery strategies in the future.

In summary, this database can provide detailed data with multiple task types, rich data dimensions, frequently updated features, and a complete overall structure. It can provide comprehensive services for dynamic scheduling models and be applied in more complex production environments. The database has been loaded into the twin system data bus to ensure consistency with the model input parameters, thereby providing systematic verification of the correctness of performance evaluations such as path generation, resource scheduling stability, and feedback control accuracy proposed and applied in subsequent research.

4.2 Data Preprocessing

The data sources collected in manufacturing enterprise information systems are highly heterogeneous, including structured task process data, semi-structured state logs, as well as unstructured environmental images, sensor signals, etc. Directly inputting them into scheduling models will lead to noise propagation, logical mismatch, and path misjudgment. Therefore, establishing a complete and refined data preprocessing mechanism is the foundation for supporting the stable operation of the digital twin driven scheduling model.

This study is based on a four-step process of "timing alignment type cleaning structure mapping input regularization" to carry out preprocessing operations, and achieves unified transformation and modeling adaptation of task data and resource status data through

an automated pipeline. Firstly, the original collected data is time series unified, and all sampled data are interpolated and aligned based on a unified time window to ensure causal consistency between cross module data in the time dimension. On this basis, fill in or logically supplement the missing fields in the task flow data (such as task start and end time, dependencies before and after), and derive the task chain path based on the enterprise BOM file and process list.

The task data cleaning stage focuses on field standardization and outlier removal. For records with abnormal fluctuations in the task execution time field, the sliding window outlier detection algorithm is used to identify and remove sampling points with a deviation rate exceeding 3 σ; The parts of the device load data that show short-term jump values are repaired using median smoothing processing. In addition, all resource data fields are uniformly converted to the standard unit system, such as unifying power information as kW and transportation delay as seconds, to ensure consistent numerical scales between input variables and facilitate subsequent model normalization processing.

Data structure mapping is a crucial step in connecting the original collected data with the input space of the scheduling model. The task flow data needs to be transformed into a graph structure, where each task node is represented by an adjacency matrix to indicate its pre - and post process dependencies, forming a scheduling dependency graph; Multi source data is organized in the form of a feature matrix, including feature dimensions such as current state, failure probability, availability, and waiting time, which are mapped as the edge weight basis for model path search. To unify the model input structure, construct the following tensor format:

$$X \in R^{T \times N \times F} \quad (5)$$

Among them, T represents the length of the time window, N represents the number of tasks or resources,

and F represents the feature dimension of each unit; This tensor is used to carry the dynamic state of tasks and resources in a multidimensional feature space. Simultaneously define the output label tensor as:

$$Y \in R^{T \times N} \quad (6)$$

Used to annotate the scheduling success and path interruption status of each task within a given time window, providing a target benchmark for the supervised learning module. This structure achieves joint modeling of task flow and resource status, supporting continuous perception and dynamic prediction of time-varying inputs by scheduling models.

In the process of scheduling modeling, in order to prevent overfitting and data redundancy, this study introduces a feature selection mechanism after constructing the input tensor. A joint evaluation index based on information gain and mutual information is used to screen out the 15 core feature fields that have the most influence on path generation, such as task expected time, current device load rate, resource switching penalty coefficient, task heat index, etc., and eliminate redundant frequency fields and redundant category variables.

For fault interference and sudden state data, in order to not destroy the original distribution characteristics, the system adopts a fault simulation label embedding strategy, which embeds interference marker bits in the input sequence for the model to automatically distinguish and dynamically adjust.De Giacomo et al. constructed a digital twin combination method for intelligent manufacturing based on Markov decision processes, highlighting the model's ability to achieve dynamic optimal scheduling in uncertain environments [18].The entire input data is standardized using Z-score to reduce the interference of dimensional differences on inference accuracy. In terms of data partitioning, dynamic sampling is performed using sliding time windows in a 7:3 ratio, while maintaining consistency in scene structure to avoid training bias.

In summary, the data preprocessing process not only needs to complete the standardized conversion of raw sensory information to the data format accepted by the model, but also needs to carry out a series of processes such as deep data cleaning, normalization, structural mapping, and label generation, which serve as key data guarantees for subsequent path generation and feedback allocation of model accuracy and stability. The process will cycle within the system's scheduling cycle, in order to continuously maintain the perception state and reception conditions of the model at the highest level.

4.3 Evaluation indicators

In order to verify the comprehensive advantages of the model constructed in this study on the scheduling efficiency and stability of the entire system, this study analyzes five aspects: task cycle, path accuracy, utilization rate, response adjustment time, and interruption probability, and compares and analyzes them with traditional MES systems and heuristic algorithms. The evaluation process is based on the dynamic manufacturing simulation system provided in this study, designing a simulation test set with resource changes in parallel standard scenarios, and then conducting 100 scheduling experiments on the designed test set to calculate the mean values of various indicators.

From the perspective of task execution time, the average completion time of this research model is 38.4 seconds, significantly lower than the 52.7 seconds of MES system and the 45.9 seconds of heuristic algorithm, which are shortened by 27.1% and 16.4% respectively. This advantage stems from the fact that the model can optimize the task chain in real-time based on twin feedback, reduce waiting and conflict time, and improve scheduling rhythm.

In terms of path accuracy, this research model achieved 91.2%, far higher than the 76.5% of MES system and better than the 84.3% of heuristic algorithm. A higher level of path matching indicates that the model can still maintain scheduling coherence, adjust path generation strategies in a timely manner, and maintain consistency in operational logic even when task states frequently change.

In terms of resource utilization, the utilization rate of this research model is 87.6%, while the MES system and heuristic algorithm are 69.8% and 78.4%, respectively. This result reflects the synergistic effect of task node structure optimization mechanism and resource allocation strategy, which can timely invest idle resources into task execution, alleviate bottleneck pressure, and achieve the improvement of multitasking concurrent processing capability.

In terms of system response speed, path adjustment delay is the core indicator for evaluating the model's adaptation speed to abnormal changes. The model adjustment delay in this study is only 1.7 seconds, compared to 6.3 seconds for MES systems and 4.5 seconds for heuristic algorithms. The main difference lies in the reconstruction method of the scheduling strategy. In this study, a state driven feedback path update mechanism is adopted, which can respond to the generation of scheduling paths at the beginning of state changes and avoid repeated calculations at intermediate levels.

The stability of system operation is reflected in the path interruption rate indicator. The interruption rate of this research model is 3.2%, while the MES system and heuristic algorithm are 11.7% and 7.6%, respectively. The low interruption rate display model has the ability to maintain the integrity of the execution chain in complex disturbance scenarios, and is less likely to cause cascading blockages due to local task failures or resource chain disruptions, ensuring production continuity.

Figure 2 presents the performance bar charts of each model on five indicators, clearly demonstrating the comprehensive advantages of this research model in terms of task efficiency, path accuracy, resource coordination, response speed, and system stability.

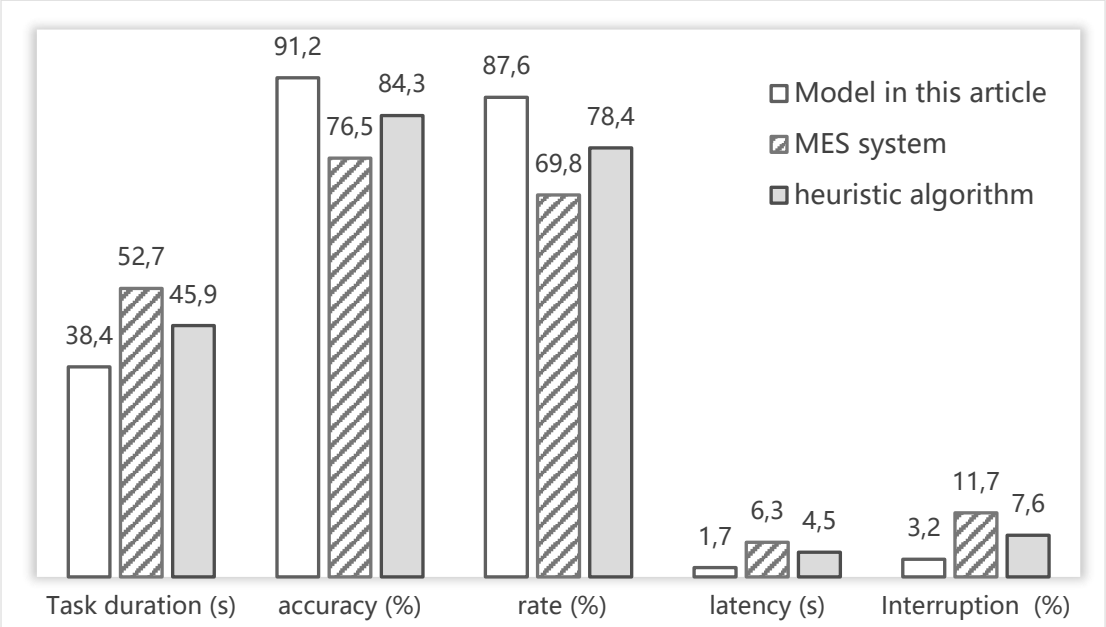

Figure 2：Bar chart of comparative performance of various scheduling models on five indicators

Based on the above evaluation results, this research model demonstrates strong adaptability and high robustness in the scheduling process, and can support dynamic task coordination and resource optimization in multi task intensive manufacturing scenarios. It has good scalability in practical applications, providing a feasible path and engineering support for the innovation of scheduling mechanisms in intelligent manufacturing environments.

4.4 Ablation study

To further verify the specific roles of each core component in the overall performance of the model, this section designs multiple ablation experiments to strip the key structures in the digital twin model and observe their impact on indicators such as task efficiency, path accuracy, and resource utilization. By comparing the execution results of the "complete model" and various simplified versions under the same manufacturing simulation task set, clarify the contribution of each module in scheduling optimization.

The experiment adopts four sets of model configurations: one is to remove the dynamic feedback mechanism and only retain the static path execution logic; The second is to eliminate the state synchronization mechanism, and the model cannot obtain real-time resource information; The third is to not use node structure optimization and only retain the traditional task flow description method; The fourth is the final model version that fully integrates path awareness, task modeling, and state linkage mechanisms. Each model was run 100 rounds on the same task sample set, and key indicators such as task completion time, path accuracy, and resource utilization were recorded. The data is shown in Table 4.

Table 4：Comparison of key performance indicators for ablation test

Ablation item	Task completion time (s)	Path accuracy (%)	Resource utilization rate (%)
No dynamic feedback	49.3	72.5	67.3
Stateless synchronization	46.7	78.9	73.8
Node free structure optimization	44.1	83.2	80.4
complete model	38.4	91.2	87.6

Experimental data shows that in the absence of a dynamic feedback mechanism, the model's response to issues such as task anomalies and path conflicts lags behind, resulting in a significant increase in task completion time, a decrease in path accuracy to 72.5%, and a resource utilization rate of only 67.3%. This indicates that the system lacks the ability to immediately correct its operating status and is prone to path redundancy and resource idleness.

After the state synchronization module is removed, the model cannot dynamically obtain the load changes of devices or nodes in path planning. Although the task structure is maintained, path decision delay and resource mismatch problems increase, resulting in performance indicators that are slightly better than the former but still insufficient. The task completion time was 46.7 seconds, the path accuracy decreased to 78.9%, and the resource utilization rate was 73.8%.

If the node structure optimization module is not introduced, the system will have insufficient decoupling of task logic, and the scheduling path will tend to be linear, which will affect the parallel ability of tasks. In the experiment, the task completion time of the configured group was reduced to 44.1 seconds, but the path accuracy and resource utilization only increased to 83.2% and 80.4%,

respectively, indicating that the insufficient depth of structural modeling restricts the flexibility of path generation.

In contrast, the complete model integrates three core mechanisms: dynamic feedback, state synchronization, and node optimization, which can effectively coordinate task execution progress and resource allocation status, and achieve path adaptive reconstruction and real-time policy updates in a dynamic environment. The task completion time of this experiment was shortened to 38.4 seconds, the path accuracy was improved to 91.2%, and the resource utilization rate reached 87.6%, performing the best among all configurations.

The results indicate that the synergistic effect of the three core modules is the key foundation for achieving efficient scheduling. Although each mechanism has differences in the magnitude of indicator improvement, they all play an important supporting role in the overall performance of the model and are indispensable. Especially in the face of complex and ever-changing manufacturing scenarios and frequent disturbances, the linkage between modules has an amplifying effect on the improvement of stability and efficiency.

Although the complete model performs the best overall on the three core indicators, some ablation models also approach the complete model in certain dimensions (such as task completion time under "no node structure optimization"), suggesting that this dimension may have limited impact on some scheduling processes. In addition, the "no dynamic feedback" model showed a significant decrease in path accuracy and resource utilization, reflecting the key role of this mechanism in maintaining execution coherence and resource allocation. Overall, the experimental results have formed a consistent supporting logic among the core modules, and the data and model functional performance maintain a good correspondence.

In summary, the ablation experiment results clearly indicate that the proposed dynamic feedback mechanism, state synchronization module, and task node structure modeling all play a key role in the overall performance of the model. The collaborative operation of the three parties to build an adaptive, highly responsive, and high-precision scheduling system is the core pivot for achieving a leap in the dynamic control capability of manufacturing enterprise information systems. The absence of any module will lead to the decline of task execution efficiency, inaccurate path decision or unbalanced resource use, which verifies the technical rationality and engineering practicability of the research model in terms of structure construction and function integration. The above verification provides a solid basis for subsequent system deployment and operation mechanism optimization, and further solidifies the reliability foundation of the model in real manufacturing scenarios.

Compared to most existing digital twin systems that mainly rely on static modeling and visual feedback, the dynamic operation and control model proposed in this paper has undergone substantial optimization in terms of structure and mechanism design. The model achieves dynamic perception and response control of the operating status of manufacturing enterprises by introducing multi-source heterogeneous data fusion, task state adaptive regulation, and closed-loop governance linkage mechanism. This model effectively breaks through the technical bottlenecks of feedback delay and decision isolation in current digital twin systems, providing a more real-time and flexible support path for the intelligent upgrade of complex manufacturing systems.

5 Discussions

5.1 Performance advantage analysis of existing dynamic scheduling methods

Compared with the current state monitoring driven manufacturing system construction method, the model proposed in this paper has three improvements: ① introducing a multi form task push mode to enhance task scheduling accuracy and implementation flexibility, ② establishing a consistency system of twin mapping and control feedback to improve responsiveness, ③ proposing a three-dimensional interactive dynamic optimization execution strategy to make execution more effective. These improvements have exceeded the scope of traditional process control models and are a good demonstration of the model's adaptation to the characteristics of intelligent production modes.

The dynamic scheduling methods commonly used in traditional manufacturing enterprises, such as rolling time windows, task priority, and rule triggering mechanisms, have certain management effectiveness under low-frequency disturbances. However, in environments with high task parallelism, strong resource competition, and unstable device states, problems such as strong path rigidity and slow response occur frequently.Shen B proposed a digital twin framework based on edge cloud collaboration for real-time production control, which improves the visualization level, response speed, and control intelligence of manufacturing systems through a layered architecture [19].

The digital twin driven operation and control model proposed in this study demonstrates significant advantages in three aspects.

One is that in terms of scheduling response mechanisms, traditional methods mainly rely on event triggering and lack continuous perception of system status. This research model achieves real-time synchronization between task progress and resource status through twin mapping, allowing scheduling strategies to be dynamically and automatically adjusted with the system, achieving continuous feedback and policy linkage, breaking the constraints of static rules on the execution process.

Secondly, in terms of path planning and task matching accuracy, traditional algorithms are mostly dominated by priority and have a single path planning strategy. In contrast, this research model constructs a state aware path generation mechanism that combines task dependency relationships and resource graphs to support dynamic reconstruction of the shortest time-consuming path. In the evaluation of Chapter 4, the path matching rate reached 91.2%,

significantly better than the heuristic method's 84.3%, demonstrating stronger scheduling adaptability.

Thirdly, traditional resource scheduling and system stability mainly consider local optimization rather than the overall load of resources, while the model proposed in this study can implement real-time resource adjustment strategies to avoid bottleneck conflicts and fully utilize resources. After testing, the model can achieve an effective resource utilization rate of over 87.6%, while the path interruption rate is only 3.2%, which is better than existing MES systems and heuristic algorithms, demonstrating good system flexibility and stability.

In addition, the average task completion time is only 38.4 seconds, which is 27.1% shorter than the MES system, demonstrating a significant optimization effect of the scheduling mechanism on task completion efficiency.

In summary, compared with current mainstream methods, this research model has advantages in four dimensions: accuracy of scheduling, coordination of the system, dynamic optimization of resource allocation, and stability of the scheduling system. It also demonstrates the technical advantages brought by the digital twin architecture, which can provide a feasible path for manufacturing intelligent and flexible scheduling systems.

5.2 Model adaptability and stability verification under complex operating conditions

The manufacturing site is highly dynamic and environmentally uncertain, and traditional scheduling methods are prone to losing control in situations such as resource anomalies, path failures, or sudden tasks. To verify the adaptability and stability of the constructed digital twin driving model under complex working conditions, this study sets four typical disturbance conditions, namely sudden task changes, resource failure switching, high concurrency scheduling, and path constrained reconstruction. Perform 100 rounds of task scheduling experiments for each scenario, collecting three core indicators: successful scheduling rate, average task delay, and system stability score. The results are shown in Table 5.

Table 5: Comparison of model scheduling performance under typical complex operating conditions

Test scenario	Successful scheduling rate (%)	Average task delay (s)	Stable score (10)
Sudden changes in tasks	92.5	3.4	9.1
Resource failover	89.7	4.1	8.8
Scheduling high concurrency	90.8	3.9	8.9
Path restricted reconstruction	88.3	4.6	8.5

In the scenario of "sudden changes in tasks", the model can quickly identify the impact of new tasks and adjust the scheduling diagram structure through global state perception and node dependency tracking of the twin system. The success rate is as high as 92.5%, with an average delay of only 3.4 seconds. The system's continuity score is 9.1, reflecting its ability to dynamically integrate sudden tasks.

In the "resource failover" test, the model utilizes the device twin feedback mechanism to replace redundant paths and readjust available resources, ensuring overall system smoothness. Although the temporary reconstruction of the scheduling path introduced a certain delay (averaging 4.1 seconds), the success rate still reached 89.7%, with a stability score of 8.8, reflecting strong anti-interference and modular emergency response capabilities.

In the scenario of "scheduling high concurrency", multiple task streams simultaneously request execution channels, and the system implements task peak shaving and valley filling through a hierarchical scheduling mechanism of node priority and resource concurrency pool. The success rate is 90.8%, the average delay is controlled within 3.9 seconds, and the stable score is 8.9, indicating that the system can maintain scheduling continuity and a reasonable and orderly task queue.

In the context of "path constrained reconstruction", the model dynamically evaluates the remaining feasible paths and generates real-time suboptimal solutions to replace the main path. Although the success rate slightly decreased (88.3%), the system did not experience any interruptions or path crashes, with an average delay of 4.6 seconds and stability still maintained at 8.5, verifying its path network resilience and reconstruction adaptability.

Overall, the constructed model can still maintain a scheduling success rate of over 88% and a response time of less than 4.6 seconds, driven by high-frequency task changes, dynamic resource regulation, and path fault-tolerant reconstruction, with a stability score of 8.5. The system adopts a closed-loop approach of state perception, graph reconstruction, and feedback correction, combined with a multi-layer scheduling structure and high-frequency data update mechanism, and has good adaptability.Fekete et al. validated the high fidelity capture capability of twin systems for geometric deviations and actual responses, providing experimental support for maintaining performance under complex operating conditions[20].

5.3 Feasibility assessment of system resource expenditure and manufacturing scenario deployment

In the process of digital transformation of manufacturing enterprises, the implementation effect of intelligent models highly depends on their adaptability to computing resources, communication capabilities, and operating platforms. Therefore, conducting resource cost and deployment

feasibility assessments of dynamic operation and control models in typical manufacturing scenarios is a key step in measuring their engineering potential.

This model consists of three major modules: edge perception, central decision-making, and twin interaction. Edge modules are deployed on industrial terminals or gateways, responsible for device data collection and preliminary processing. In the scenario of 10Hz sampling frequency and hundred level concurrent tasks, the CPU usage of a single node is controlled within 35%, and the memory requirement is about 1.2GB. It can run stably in mainstream PLC or ARM devices without the need for high-end hardware support.

The central module adopts GPU architecture to complete path generation and feedback inference tasks. In a typical scenario, the scheduling cycle is 2.1 seconds, and the path calculation time accounts for nearly 60%. Experimental verification shows that GPU servers with moderate configurations (such as RTX A2000) can stably support real-time scheduling with a task scale of 100 tasks, and also provide lightweight versions to adapt to computing limited environments.

The twin interaction module is based on WebSocket to achieve state synchronization and visual output. At 1080p resolution, the bandwidth overhead is about 4.2Mbps, and the communication delay is less than 200ms, meeting the basic requirements of industrial networks for real-time performance and stability.

For production environments with small production scales (20 job positions, 100 production tasks), the overall investment of the system is controlled within 400000 yuan, including the cost of software and hardware purchase and integration, which is lower than the average level of most similar digital factory solutions. The system structure has good flexibility and modular expansion capabilities, which can meet the needs of enterprises of different sizes.

Finally, the model seamlessly connects with mainstream systems such as MES, ERP, SCADA through standard interfaces, avoiding information isolation and integration difficulties. The model also has remote maintenance and module hot plugging functions, making it easy for enterprises to flexibly update, upgrade, and dynamically adjust according to their own needs, improving overall operation and maintenance efficiency and cost return.

In summary, the model constructed in this study can effectively control resource costs, has good compatibility, and saves economic deployment costs. It can be applied and promoted in the production field, providing solid support for promoting the construction of digital intelligent control system.

5.4 Application value of the model in the digital transformation of manufacturing enterprises

In order to meet the digital transformation needs of manufacturing enterprises and the requirements of multi-objective processing in complex work environments and task scenarios, this study establishes a dynamic operation management model based on digital twin technology and introduces optimization paths and status monitoring mechanisms, which have demonstrated significant value in various manufacturing environments.

From the perspective of model running efficiency, by re establishing the scheduling diagram and improving the path method, resource competition and path collision have been effectively avoided. The scheduling response time during actual operation has also been reduced to less than 2 seconds, and the resource utilization rate has been maintained at over 85%, greatly improving the alignment between job pace and work efficiency. The system has high fault tolerance, can distinguish between task delays and equipment failures, and can quickly re formulate scheduling strategies to maintain stable operation. According to the company's implementation data, the number of unplanned shutdowns has decreased by 40%, the success rate of task execution has increased to 93%, the number of scheduling conflict alerts has also been significantly reduced, and maintenance pressure has been correspondingly alleviated.

In terms of management, the digital twin platform on which the model relies displays the production process of the model in a visual manner. Scheduling nodes, resources, and bottleneck information can all be viewed in a timely manner through images, making it easy to make precise decisions and judge future trends. This has achieved a transformation from an experience driven management model to a new management model based on data analysis.

The wide compatibility of system interfaces further enhances its promotional value. The model can be integrated with multiple systems such as MES, ERP, SCADA, etc., supporting remote and functional deployment, adapting to different types of production and enterprises of different scales, reducing redundant construction and information silos, and increasing the execution flexibility of the model.

In summary, the research model has high adaptability and effectiveness in terms of scheduling performance, system stability and reliability, management system operation efficiency, and system platform openness. It is an important auxiliary tool for manufacturing enterprises to implement intelligent transformation and upgrading, and an effective way to achieve flexible production in manufacturing enterprises. It provides a feasible path for achieving flexible production and efficient control.

6 Conclusion

This study focuses on the dynamic operation and control model of enterprises driven by digital twins, and constructs a three-layer architecture consisting of an integrated edge perception layer, a central decision-making layer, and a visual interaction layer to improve the execution efficiency and response stability of manufacturing systems. The research is based on model design structure and scheduling scheme, clarifying the coupling logic between various functional modules, and quantitatively analyzing key parameters such as task completion time, path matching, and resource utilization rate in simulation experiments, proving the practical feasibility of the model in multi task

intensive scenarios. In terms of economic evaluation, the system can achieve modular access to meet any needs, reduce usage costs, and has strong promotion potential and investment cost-effectiveness. Overall, this model can effectively optimize production processes, ensure operational stability, and accelerate the development process of intelligent manufacturing, providing a practical path and theoretical support for building efficient, collaborative, and visible operational mechanisms for digital factories.

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A Two-Tier Energy-Aware Resource Allocation Framework in Cloud Computing Using the Spider Wasp Optimizer

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Cloud infrastructures are increasingly subject to performance and environmental requirements, particularly in large data centers with substantial energy expenditures. This paper addresses the issue of energy-aware quality of service (QoS) guaranteed resource allocation and presents an original two-tiered resource allocation scheme based on a Green Management Module (GMM) and a Spider Wasp Optimizer (SWO)-driven Cloud Management Module (CMM). The CMM pre-filters candidate resources based on the latest measurements beforehand, and the GMM selects the optimal resource, aided by the SWO, to inform the allocation decision. Experimental results show that the scheme reduces service response time and energy consumption by 25% and 26% compared to baseline schemes such as dynamic VM provisioning and VM allocation policies. The scheme presents an energy-aware and scalable design with tremendous prospects for optimizing resource use in existing clouds.

Povzetek: Članek predstavi dvostopenjski, na energijo občutljiv okvir razporejanja virov (CMM+GMM) z metaheuristiko Spider Wasp Optimizer, ki v simulacijah skrajša odzivni čas in porabo energije v oblačnih podatkovnih centrih.

1 Introduction

1.1 Context

Computers and cell phones have proliferated worldwide over the last two decades. Due to this, competition among companies has also increased, and more emphasis has been placed on expanding into new geographical territories to ensure sustainable profitability [1]. To effectively adapt to these changing demands and achieve optimal operational efficiency, improvements in resource utilization are necessary [2]. Cloud computing offers consumers a diverse set of unlimited computing resources tailored to their individual needs. These are accessed instantly at any time and from any location. This is achieved by a pay-per-use system where customers are only charged for the services they actively use [3]. Recent advancements in related domains, such as the use of machine learning for analyzing economic factors [4], optimal allocation strategies for energy and infrastructure in microgrids [5, 6], and intelligent security systems for dynamic network environments [7], highlight the potential of computational intelligence in addressing complex operational challenges. These developments collectively demonstrate how optimization, predictive analytics, and adaptive control can be integrated into cloud-based solutions to improve efficiency, security, and sustainability.

The cloud provides resources with consolidated horizontal and vertical scaling, as well as flexible or elastic functions, which prevent businesses from paying for resources that are not being used. Additionally, the flexibility and scalability of cloud services enable companies to quickly adapt to changes in market demand [8]. Such agility will foster improved innovation and competitive advantages. Central management of cloud infrastructure makes cloud infrastructure provision easier [9]. Both cloud service providers and customers can manage resources more effectively by adopting virtualization technology and implementing dynamic resource scheduling strategies [10].

1.2 Problem statement

Efficient resource allocation would minimize job execution time, maximize resource utilization, and reduce resource consumption. The task scheduling aspect has been considered paramount in cloud data centers to mitigate resource constraints resulting from increased workload [11]. The allocation of tasks to cloud resources to meet scheduling objectives and optimize QoS metrics remains a complex and evolving challenge in cloud computing. Recent research [12, 13] further investigates this aspect, highlighting the challenges of balancing cost, energy efficiency, Service Level Agreement (SLA) satisfaction, and dynamic workload variability. The primary scheduling issue is determining the right resource

to accomplish tasks. Scheduling algorithms can enhance most of the QoS factors, namely, execution cost, energy consumption, reliability, task rejection rate, and resource efficiency. At the same time, it guarantees compliance with SLAs while considering constraints such as deadlines, priorities, and the need to resolve load imbalance issues affecting overused and underutilized resources [14].

The growth of cloud computing infrastructure and the expansion of data centers over the past few years underscore the importance of energy conservation in cloud computing environments [15]. As is well known, data centers consume a substantial amount of energy, resulting in increased operational costs and environmental damage [16].

Energy consumption in cloud data centers has become a critical concern due to its economic and environmental impact. As cloud services scale globally, data centers are consuming increasingly large amounts of electricity, estimated to account for nearly 1% of global electricity demand [17]. Not only does it result in exceedingly high cloud operation expenses, but it is also a significant contributor to carbon emissions and climate change. According to [18], unsustainable energy consumption in data centers negates the goals of green IT and necessitates effective allocative efficiency mechanisms. Therefore, it is needed to develop QoS-aware and energy-saving resource allocation systems to achieve scalable, affordable, and environmentally friendly cloud infrastructure.

1.3 Contribution

This paper proposes an innovative resource allocation approach to maximize energy savings in cloud computing settings. It combines two modules, namely green management and cloud management. The first module finds appropriate resources from the existing pool. In contrast, the subsequent module further narrows down this selection to establish the most efficient allocation of resources in terms of power consumption. The proposed method significantly reduces average service response time using this two-tiered approach. This research makes several contributions to the field.

- Enhancing server status analysis efficiency by grouping cloud servers based on their geographical proximity;
- Optimizing service provisioning time by assigning the most suitable servers, taking into account multiple parameters;
- Promoting energy efficiency by allocating the most appropriate cloud server for each task;
- Leveraging metaheuristic algorithms to select appropriate cloud resources effectively.

To guide this study, we formulated the following research questions:

- Can a two-tier resource allocation framework improve both energy efficiency and QoS in cloud computing environments?
- Does the Spider Wasp Optimizer (SWO) outperform traditional metaheuristic algorithms in optimizing energy-aware resource allocation?

Correspondingly, we test the following hypotheses:

- The proposed two-tier framework significantly reduces average service response time compared to baseline methods.
- The SWO algorithm yields superior energy-saving performance by achieving more efficient resource utilization than existing.

While this research focuses on improving energy efficiency and service responsiveness, two of the most pressing challenges in cloud computing, it is essential to acknowledge that resource allocation can also pursue additional objectives. These include cost reduction, fault tolerance, security, scalability, and load adaptability, all of which are critical depending on the application context. Although these goals fall outside the scope of this study, the proposed method could be extended in future work to incorporate multi-objective optimization frameworks that address such concerns in parallel with energy and QoS goals.

2 Related work

As highlighted in Table 1, energy consumption and resource allocation in cloud computing have made significant advancements. Various approaches have been proposed to minimize energy consumption and optimize resource usage.

Nguyen and Cheriet [19] introduced an environmentally conscious virtual slice framework that increases energy efficiency while accounting for the intermittent nature of renewable energy sources. Virtual Machine (VM) deployment and traffic management within a virtual data center are optimized based on traffic volume, VM placement, bandwidth, and available renewable energy resources. A solution to the virtual slice allocation problem was developed by studying various cloud consolidation strategies. Based on simulations of the GSN network, it was found that the model is better at reducing the network footprint than existing methods.

Yang, et al. [20] have developed an efficient and environmentally friendly virtual data center framework and introduced two energy-efficient embedding algorithms. To evaluate the proposed algorithms, extensive simulations were performed across network scales and topologies. Compared with current embedding techniques, the adoption rates of virtual data centers, the long-term revenue of cloud service providers, energy consumption in low-utilization environments, and revenue generation in high-utilization cloud data centers were analyzed.

Khosravi, et al. [21] modeled the total energy cost by combining the server's direct energy consumption with the PUE-based overhead, considering the IT load and outside temperature. The model also finds integrating renewable energy sources into data center locations, reducing dependence on traditional, carbon-intensive grid power. By comparing various VM placement strategies, researchers determined important parameters influencing

total energy consumption (renewable and non-renewable), emissions, and costs. The study verifies the supremacy of a method that considers dynamic overall energy consumption, available renewable energy, and PUE while ensuring service level agreements.

Wu, et al. [22] developed a novel two-stage adaptive VM workload prediction model that exploits the inherent regularity of command-line applications. This model enables elastic allocation of CPU and memory resources for VMs. Departing from the ordinary time series forecasting, natural language processing extracts and handles feature attributes from command-line applications, aided by feature reduction through gray relational analysis. The prediction model uses a Bayesian classifier to identify applications that incur significant CPU increases and an adaptive neuro-fuzzy inference system to predict CPU and memory intensity. The elastic resource provisioning strategy was proved and tested through detailed experiments, which confirmed the successful completion of VM performance and resource efficiency with the scheme.

Al-Wesabi, et al. [23] presented a hybrid meta-heuristic approach for optimizing resource allocation and energy efficiency in the cloud computing context. Their methodology begins with extracting relevant features from the customer's task requirements, followed by dimensionality reduction using principal component analysis. The range of function outputs shows the optimal resource allocation. The core of their solution is the hybrid algorithm, developed based on Group Teaching Optimization (GTO) and Rat Swarm Optimization (RSO) algorithms. The hybrid scheme optimizes the resource allocation between the VMs in the cloud data center. The improved performance of the proposed model was demonstrated through rigorous simulation, conducted with the aid of the CloudSim simulator, across various performance indicators.

Tai, et al. [24] developed an original approach to increase resource allocation and energy efficiency in heterogeneous data centers within the vision of Green IT. Their procedure involves modeling energy consumption over time, inter-task dependency, and data backup necessity. Framing the issue as an energy conservation problem that is nonlinear and complex, the researchers employed mathematical programming and Lagrangian relaxation to formulate an energy conservation solution. The procedure optimally allocates computational resources, schedules tasks, and reduces energy consumption, with the advantage of achieving highly achievable performance levels in cloud data centers.

Sharma and Rawat [25] developed a novel hybrid approach by coupling the Spotted Hyena Optimizer (SHO) and an Artificial Neural Network (ANN) to address the problem of VM allocation. The new method was validated with the most significant performance indicators, which included migration number, SLA violation, execution times, resource consumption, and energy consumption. The SHO algorithm was employed to generate an overall dataset, thereby enhancing the accuracy of the ANN model. The hybrid scheme demonstrated improved convergence and global optimality compared to IqMc, SHO, and Genetic algorithms under real and simulated workload behavior.

Gurusamy and Selvaraj [26] introduced a novel framework: resource allocation in cloud computing with a multi-level auto-associative polynomial convolutional neural network. The approach combines Starling Murmuration Optimizer (SMO)-inspired short-term scheduling with the objective of reduced makespan and optimized throughput. Resource management is carried out using a HAPCNN (Hierarchical Auto-Associative Polynomial Convolutional Neural Network) module, taking into account bandwidth and resource loading limitations. Data privacy is ensured with Fractional Discrete Meixner Moments Encryption (FDMME).

Table 1: Previous research on energy-efficient resource allocation in cloud computing

Study	Algorithm type	Optimization goals	Computational overhead	Key outcomes	Comparison with the proposed method
[19]	Heuristic	Energy efficiency (using renewable energy)	Medium	Reduces network footprint	No hierarchical optimization; less responsive to real-time load
[20]	Heuristic	Energy usage, revenue, and adoption rate	High	Better embedding in VDCs	Not metaheuristic; lacks fine-grained optimization
[21]	Analytical model	Energy + carbon cost	Medium	Accounts for PUE and renewables	Requires real-time environmental data integration
[22]	Hybrid (NLP + ANFIS)	VM performance and resource use	High	Elastic VM allocation	High complexity, no focus on metaheuristics
[23]	Metaheuristic (GTO + RSO)	Resource allocation and energy efficiency	Medium	Validated via CloudSim	Does not integrate real-time queue and location metrics
[24]	Mathematical programming	Scheduling + energy use	High	Green-aware task allocation	More static and centralized vs. dynamic SWO
[25]	Metaheuristic + ANN	VM allocation, SLA, and energy usage	Medium	Improved convergence	Relies on extensive ANN training data
[26]	CNN + SMO	Resource utilization and task scheduling	Very High	Strong security and good throughput	High computational cost and complexity

Proposed	Metaheuristic	Response time, Low energy usage, and resource utilization	25% ↓ in response time and 26% ↓ in energy use	Two-tiered, scalable, low-overhead solution with real-time adaptation

While the available work has made immense contributions to energy-efficient VM placement and green cloud policies, there are still some gaps. Most approaches employ non-scalable hierarchical decision hierarchies or static/algebraically tuned algorithms that may converge too abruptly or exhibit inefficient load balancing. Additionally, very few integrate geo-awareness, online queue behavior, and adaptive metaheuristics under the same umbrella. Through the implementation of the two-tier hierarchical structure (CMM-GMM) along with the introduction of the SWO, the proposed approach eliminates the loopholes in achieving optimal QoS and optimal energy consumption.

3 Proposed resource allocation strategy

This section describes a novel resource provisioning method designed to achieve maximum energy efficiency and QoS levels in cloud environments. The intensified environmental crisis, primarily caused by human-made processes and technological advancements, demands sustainable and feasible solutions. Even as cloud computing provides unique efficiency and scalability, it has inadvertently contributed to the carbon footprint by increasing the number of data centers. Given this reality, it is imperative to devise carbon-cutting methods to offset environmental destruction caused by cloud computing.

Energy efficiency in cloud computing requires the optimal allocation of resources. When resources are allocated effectively, service requests can be fulfilled promptly while minimizing energy consumption. Load balancing between cloud servers reduces underutilization and overload, thereby reducing energy consumption. Our research utilizes SWO to determine the optimal resource configurations based on the utility level.

Here, the utility level is an application-independent indicator of the volume of resource utilization, calculated from the readings of the CPU, memory, and the number of active tasks for each interval. Utility level is an abstract representation of the amount of resource utilization, with no dependency on the type of application or the application's semantics being executed on the VM. This enables the SWO algorithm of the GMM to optimize resource provisioning based on the observable level of the system's performance and non-application-centric information, while maintaining a general and flexible architecture design.

SWO was selected due to its hunting- and escape-inspiration adaptive mechanism, offering the best compromise between exploration and exploitation in complex search spaces. Relative to Particle Swarm Optimization (PSO), which is subject to the chance of premature convergence in multimodal areas, and Ant Colony Optimization (ACO), which is underpinned by stochastic path dependency and pheromone updating with the potential to become prohibitively costly, the biologically rooted nest and mating phases of SWO enable more stable diversification of solution and management of convergence. Both global and fine-grained resource configuration refinement is offered, which is necessary in dynamic clouds.

As shown in Figure 1, to facilitate effective resource allocation and sustainable environments, a two-level architecture is proposed that comprises a Green Management Module (GMM) and a Cloud Management

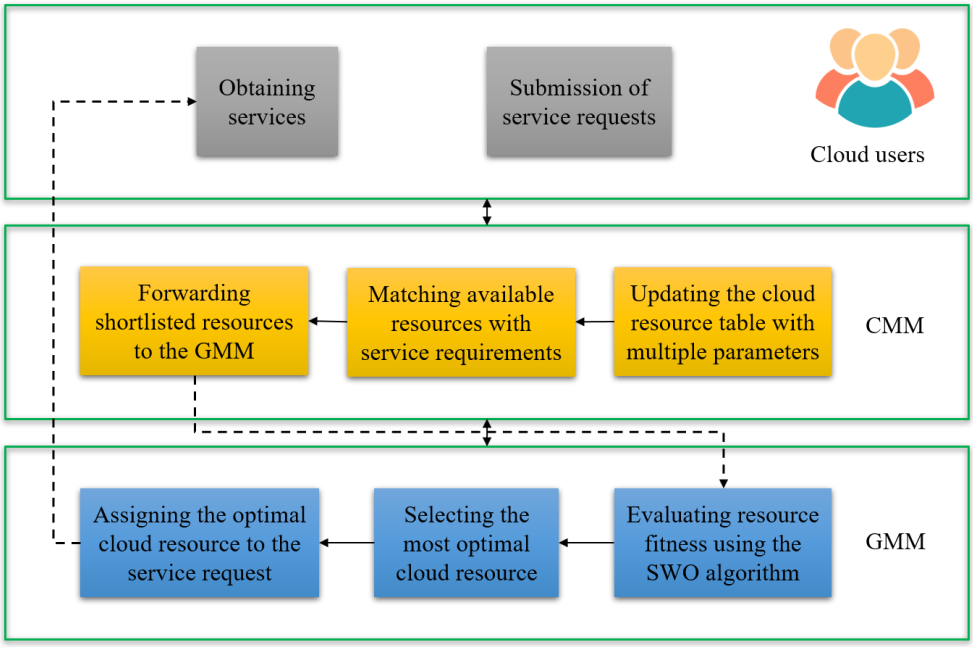

Figure 1: Two-tier architecture for energy-efficient cloud resource allocation

Module (CMM). The GMM maintains a global snapshot of locations and execution states for cloud data centers, while the CMM facilitates the balanced distribution of service requests across available resources.

The CMM serves as a management layer responsible for monitoring available system resources. The CMM optimizes VM placement and resource selection based on measurable system indicators (e.g., queue length, service response time, distance), without requiring visibility into the internal behavior of VM workloads. A cloud data center, a fundamental part of the infrastructure, consists of multiple cloud servers, each of which can host multiple VMs. Equations 1–3 define distinct identifiers for VMs, servers, and data centers.

$$VM = \{vm_1, vm_2, \dots, vm_n\} \quad (1)$$

$$CS = \{cs_1, cs_2, \dots, cs_n\} \quad (2)$$

$$CDC = \{cdc_1, cdc_2, \dots, cdc_n\} \quad (3)$$

A VM is explicitly named $vm_i^{cs_i}$, indicating its association with the cloud server instance cs_i. This nomenclature enables efficient VM identification and management. The CMM maintains a comprehensive database containing details of all cloud data centers, servers, and VMs. This repository includes attributes such as geographical coordinates, queue length, average service response time, service type, and capacities. Dynamic metrics, such as queue length and response time, are updated in real-time within the CMM to reflect system changes.

The system's workload mainly consists of VM requests initiated by cloud users. The CMM optimizes VM placement and resource allocation without requiring knowledge of the specific applications running in the VMs. Nevertheless, each VM is assumed to operate at maximum capacity and fully utilize the allocated computing resources.

To enhance the QoS of the system, the queue length and service response time are integrated. The overall response time is calculated according to the estimated average duration between consecutive service completions, as defined in Eq. 4, where SR_{time} represents the service response time, *n* refers to the overall number of tasks processed by a particular VM, and SQ_{time} denotes the time taken to complete the service request. Ideally, response time should be minimized to ensure optimal performance. Eq. 5 shows the queue length dynamically adjusted by increasing upon new requests and decreasing upon service completion.

$$ASR_{time} = \frac{\sum_{i=1}^{n}(SR_{time} - SQ_{time})}{Total\ handled\ services} \quad (4)$$

$$QL = \begin{cases} New\ service\ request: QL + 1 \\ Responded\ service: QL - 1 \end{cases} \quad (5)$$

The CMM prioritizes the selection of machines for incoming service requests based on queue length, response time, and geographical distance. The module selects the potential hosts and sends the most appropriate choices to the GMM for further processing.

The GMM's task is to identify the optimum VM to handle service requests. The CMM submits a list of probable candidates to the GMM, and the SWO algorithm determines the best machine from the list. SWO is a metaheuristic algorithm inspired by the hunting, nesting, and parasitic behavior of particular wasp species. The algorithm's basic principles are based on observing female spider wasps that search for, paralyze, and transport spiders to their nests, ultimately laying an egg in the paralyzed prey.

The SWO algorithm initiates the simulation by placing a population of randomly distributed virtual wasps in the search region, thereby modeling the foraging behavior of wasps in their surroundings. The virtual wasps search in a manner analogous to wasp foraging behavior for optimal solutions to problems. When an effective solution is encountered, the algorithm replicates the wasp's capturing and carrying away of their catches through adjusting the solution according to predetermined rules. The essential behavioral components for the SWO algorithm are as follows:

- Searching: Simulates the wasp's initial exploration of the environment to locate potential solutions.
- Following and escaping: Models the wasp's pursuit of prey, incorporating evasion tactics.
- Nesting: Represents the process of constructing a solution by combining and refining existing components to create a new, more comprehensive one.
- Mating: Incorporates a mating mechanism inspired by the wasp's reproductive strategy, utilizing a uniform crossover operator to generate new solutions.

In the SWO framework, each female spider wasp is mathematically represented as a D-dimensional solution vector (Eq. 6). An initial population of *N* such vectors is randomly generated within predefined upper (*H*) and lower (*L*) parameter limits, as shown in Eq. 7. The whole initial population is called SW_{Pop}, with individual solutions stochastically generated according to Eq. 8.

$$\overrightarrow{SW} = [x_1, x_2, x_3, \dots, x_D] \quad (6)$$

$$SW_{Pop} = \begin{bmatrix} sw_{1,1} & sw_{1,2} & \dots & sw_{1,D} \\ sw_{2,1} & sw_{2,2} & \dots & sw_{2,D} \\ \vdots & \vdots & \vdots & \vdots \\ sw_{N,1} & sw_{N,2} & \dots & sw_{N,D} \end{bmatrix} \quad (7)$$

$$\overrightarrow{SW_i^t} = \vec{L} + \vec{r} \times \left(\vec{H} - \vec{L}\right) \quad (8)$$

Where *t* represents the generation index and *i* represents the population index (in the range from 1 to *N*), *r* is a D-dimensional random vector with elements evenly distributed between 0 and 1. The algorithm then simulates the hunting, nesting, and mating behavior of spider wasps to identify the optimal solution from a set of candidates determined by CMM.

The optimization process begins with a search phase, analogous to a wasp looking for prey. This exploration occurs randomly within the solution space. Once a possible solution is identified, the algorithm moves into an encirclement and pursuit phase, mimicking the wasp's predatory behavior. Finally, the wasp metaphorically

drags the captured prey, representing the identified solution, to a nest for further processing.

The exploration phase of the SWO algorithm mimics the foraging strategies of female spider wasps. In this phase, individuals traverse the search space with a constant step size, as defined in Eq. 9, in search of suitable prey. This equation updates the position of each wasp at each generation (*t*) based on the positions of two randomly selected population members (indexed by *a* and *b*) and a random motion component (μ_1) calculated using Eq. 10. Here, r_1 is a uniformly distributed random number, and *rn* follows a normal distribution.

$$\overrightarrow{SW_i^{t+1}} = \overrightarrow{SW_i^t} + \mu_1 \times \left(\overrightarrow{SW_a^t} - \overrightarrow{SW_b^t}\right) \quad (9)$$

$$\mu_1 = |rn| \times r_1 \quad (10)$$

μ_1 represents the displacement of a virtual wasp's position in the solution space during the global exploration phase. It is a D-dimensional vector that influences how far the algorithm explores new candidate solutions at each iteration. Larger values encourage exploration, while smaller values promote exploitation of local optima.

In Eq. 9, two indices *a* and *b* are randomly selected from the current population of wasp agents. These correspond to different solution vectors in the search space. The movement of a given wasp is guided by the difference between these two agents' positions, allowing the algorithm to explore based on population diversity. The update rule thus simulates a directional movement influenced by randomly selected peers and a stochastic component, which together ensure broad and adaptive coverage of the solution space.

An additional exploration strategy was incorporated because wasps can lose sight of their prey. Equations 11-13 introduce a second exploration method with a smaller step size, focusing on a randomly selected population member (*c*). This approach allows for more targeted searches around potential prey locations. *B* is the binary vector indicating the direction of exploration for each dimension. It determines whether to apply a random motion or move toward another wasp's position. Parameter *l* (uniformly distributed between -2 and 1) and random numbers r_3 and r_4 (uniformly distributed between 0 and 1) determine the choice between the two exploration methods (Equation 14).

$$\overrightarrow{SW_i^{t+1}} = \overrightarrow{SW_c^t} + \mu_2 \times \left(\vec{L} + \overrightarrow{r_2} \times \left(\vec{H} - \vec{L}\right)\right) \quad (11)$$

$$\mu_2 = B \times \cos(2\pi l) \quad (12)$$

$$B = \frac{1}{1 + e^l} \quad (13)$$

$$\overrightarrow{SW_i^{t+1}} = \begin{cases} Eq.\ 9 & r_3 < r_4 \\ Eq.11 & otherwise \end{cases} \quad (14)$$

As soon as the spider wasp discovers prey caught in its web, it launches an attack. However, the prey often escapes capture by falling to the ground. The wasp pursues the fallen prey, paralyzes it, and transports it to a prepared nest. Alternatively, the wasp may lose track of the prey while descending, requiring a simultaneous pursuit and evasion strategy.

This complex behavior can be modeled as two main trends. During the first chase, the wasp pursues the prey and captures it. This phase is represented mathematically by Eq. 15, which updates the wasp's position based on the location of the prey. Conversely, the second trend simulates escape from prey, characterized by an increasing distance between predator and prey with each iteration. This behavior can cause the prey to seek refuge in areas away from the wasp.

$$\overrightarrow{SW_i^{t+1}} = \overrightarrow{SW_i^t} + C \times \left|2 \times \overrightarrow{r_5} \times \overrightarrow{SW_a^t} - \overrightarrow{SW_i^t}\right| \quad (15)$$

Eq. 16 mathematically models predatory pursuit, where the initial proximity between wasps and prey can vary depending on their speeds. Two scenarios are considered: (1) a wasp exceeding the speed of the prey (*C* > *0.5*) and (2) a prey exceeding the speed of the wasp (*C* < *0.5*). The parameter *C*, a distance control factor initialized at two and decreasing linearly to zero, influences the wasp's speed. If *C* is greater than 0.5, the wasp is faster than its prey, representing escape behavior. On the other hand, if it is less than 0.5, the wasp's movement is significantly restricted, making prey capture more difficult.

$$C = \left(2 - 2 \times \left(\frac{t}{t_{max}}\right)\right) \times r_6 \quad (16)$$

Eq. 16 models the dynamic interaction between the predator (wasp) and its prey (candidate solution) by controlling their relative movement based on a distance control coefficient. The coefficient starts at a high value (typically 2) and linearly decreases toward zero over time (t), thereby gradually shifting the algorithm from exploration to exploitation.

The variables *a*, *t*, t_{max}, r_5, and r_6 represent a randomly selected population index, a current and maximum score, a randomly generated vector within the interval [0, 1], and a random number within the same interval, respectively.

The prey's escape from the wasp leads to a gradual increase in their distance. Initially characterized by exploitation, this phase transitions into exploration as the distance increases. Eq. 17 simulates this behavior change. The vector $\overrightarrow{vc}$, normally distributed between *k* and *-k*, and calculated from Eq. 18, the distance increases. Eq. 19 randomly determines the balance between these two behavioral trends.

$$\overrightarrow{SW_i^{t+1}} = \overrightarrow{SW_i^t} \times \overrightarrow{vc} \quad (17)$$

$$k = 1 - \left(\frac{t}{t_{max}}\right) \quad (18)$$

$$\overrightarrow{SW_i^{t+1}} = \begin{cases} Eq.15 & r_3 < r_4 \\ Eq.17 & otherwise \end{cases} \quad (19)$$

At the beginning of the optimization process, all wasps engage in global exploration of the solution space to identify promising regions with near-optimal solutions. Subsequently, an escape mechanism enables the wasp to explore and exploit its local environment, thereby avoiding local optima. Eq. 20 governs the dynamic interplay between exploration and exploitation, with the random variable *p (0 ≤ p ≤ 1)* influencing this balance. Figure 2 visually represents this compromise.

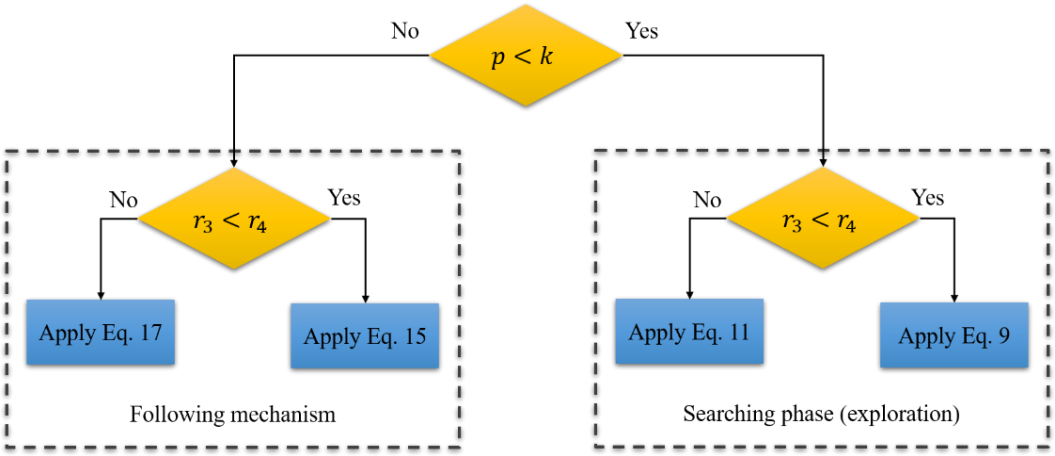

Figure 2: Dynamic balance between global exploration and local exploitation in the SWO algorithm

$$\overrightarrow{SW_i}^{t+1} = \begin{cases} Eq.14 & p < k \\ Eq.19 & otherwise \end{cases} \quad (20)$$

After immobilizing the prey, the female wasp transports it to a pre-made nest. Nest-building strategies vary and include underground burrows, aerial mud structures, or the appropriation of existing cavities. The proposed algorithm consists of two equations to simulate this diversity.

The first equation (Eq. 21) models nest site selection based on proximity to a suitable spider, referred to as the optimal egg-laying site. The term *SW** represents the best-identified solution to date. Conversely, the second equation (Eq. 22) randomizes nest placement around a selected female wasp, considering a step size to prevent nest overlap. In this equation, r_3 is a random value within the interval [0, 1], *y* is a value generated by Levy flight, *a*, *b*, and *c* are indices of randomly selected solutions, and *U* is a binary vector that controls the step size application. The binary vector *U* is determined by Eq. 23, where r_4 and r_5 represent random values in the interval [0, 1]. These two nest-building strategies are selected randomly according to Eq. 24.

$$\overrightarrow{SW_i}^{t+1} = \overrightarrow{SW}^{*} + \cos(2\pi l) \times \left(\overrightarrow{SW}^{*} - \overrightarrow{SW_i}^{t}\right) \quad (21)$$

$$\overrightarrow{SW_i}^{t+1} = \overrightarrow{SW_a}^{t} + r_3 \times |\gamma| \times \left(\overrightarrow{SW_a}^{t} - \overrightarrow{SW_i}^{t}\right) + (1 - r_3) \times \vec{U} \times \left(\overrightarrow{SW_b}^{t} - \overrightarrow{SW_c}^{t}\right) \quad (22)$$

$$\vec{U} = \begin{cases} 1 & \vec{r_4} > \vec{r_5} \\ 0 & otherwise \end{cases} \quad (23)$$

$$\overrightarrow{SW_i}^{t+1} = \begin{cases} Eq.21 & r_3 < r_4 \\ Eq.22 & otherwise \end{cases} \quad (24)$$

Eq. 25 regulates the interaction between hunting and nesting behavior, as shown in Figure 3. All wasps initially look for prey, then build nests and provide food.

$$\overrightarrow{SW_i}^{t+1} = \begin{cases} Eq.20 & i < N \times k \\ Eq.24 & otherwise \end{cases} \quad (25)$$

The SWO algorithm considers spider wasp mating behavior. A key feature of these insects is their sex determination based on host size: smaller hosts produce male offspring, while larger hosts produce female offspring. In this model, each spider wasp represents a possible solution within a generation, with the spider wasp's eggs symbolizing newly generated solutions. Eq. 26 controls the production of these offspring.

$$\overrightarrow{SW_i}^{t+1} = Crossover(SW_i^t, SW_m^t, CR) \quad (26)$$

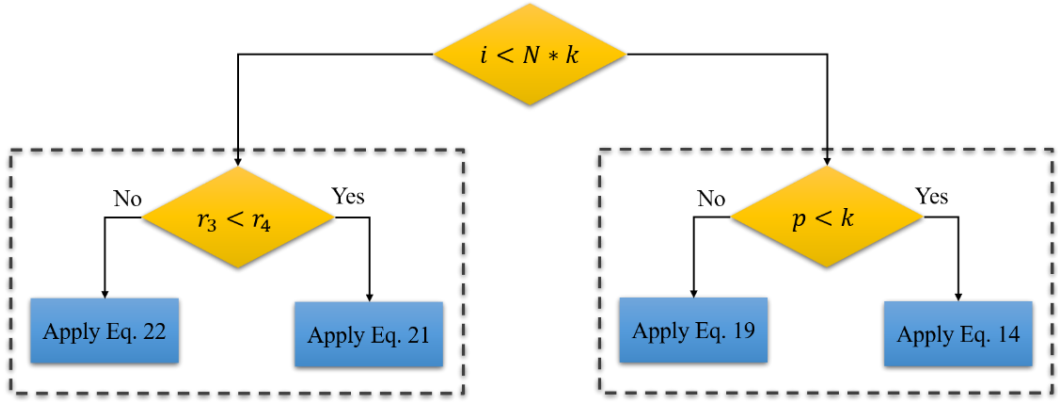

Figure 3: Interaction between hunting and nesting behaviors in the SWO algorithm

In the biological behavior of spider wasps, the size of the host determines the sex of the offspring. Larger hosts usually yield female wasps, which are most likely to survive and reproduce. The same principle is adopted in SWO to skew offspring generations in favor of high-fitness solutions. In the optimization context, a "host" represents a candidate cloud resource configuration, and its size (fitness) determines whether it should propagate high-quality traits.

During the mating phase, new candidate solutions (offspring) are created by combining "female" and "male" wasps using a uniform crossover operator. The crossover rate specifies the amount of genetic material (i.e., configuration parameters for resources) transferred from each parent. The operation injects diversity while retaining good features from high-performance solutions. Therefore, the nest-building and mate selection step in SWO approximates fine local search and solution diversification, which is pivotal for fine-tuning VM allocation strategies that conserve energy while maintaining QoS integrity.

A uniform crossover operator is applied to a parent wasp pair SW_i^t (female) and SW_m^t (male), with the probability defined by the crossover rate (CR). To distinguish male wasps from females, Eq. 27 is used, producing male wasps distinct from the female population. This equation uses normally distributed random numbers (β and β_1), the exponential constant (e), and values derived from equations 28 and 29. Crossover combines the genetic material of the parents and produces offspring that inherit their parents' traits. A predefined trade-off rate (TR) balances hunting and mating behaviors, as detailed in the experimental section.

$$\overrightarrow{SW_m^{t+1}} = \overrightarrow{SW_i^t} + e^l \times |\beta| \times \vec{v}_1 + (1 - e^l) \times \vec{v}_2 \quad (27)$$

$$\vec{v}_1 = \begin{cases} \vec{x}_a - \vec{x}_i & f(\vec{x}_a) < f(\vec{x}_i) \\ \vec{x}_i - \vec{x}_a & otherwise \end{cases} \quad (28)$$

$$\vec{v}_2 = \begin{cases} \vec{x}_b - \vec{x}_c & f(\vec{x}_b) < f(\vec{x}_c) \\ \vec{x}_c - \vec{x}_b & otherwise \end{cases} \quad (29)$$

The SWO algorithm assesses the suitability of available resources and determines the most suitable option to fulfill the service request. An initial resource selection list is created based on factors such as distance, queue length, average response time, and capacity. The GMM then examines this list to identify the optimal resource using a fitness function, as formalized in Eq. 30.

$$F = \frac{Total\ service\ requests \times Total\ energy\ used}{Utility\ degree} \quad (30)$$

4 Performance evaluation

The proposed approach considers three key metrics: average service response time, throughput, and energy consumption. These critical metrics have been chosen for their paramount importance in computing efficiency, overall scalability, and power consumption in computational cloud solutions, using their vital analysis to prove the given problem. The proposed method is compared with existing methods, namely dynamic VM allocation, VM provisioning, and data center provisioning, to validate the model. These approaches represent conventional techniques used in real-world systems. The results showed that the latter proved the model's superiority, particularly in optimizing QoS while significantly reducing energy consumption.

All experiments were conducted using CloudSim 3.0.3, a simulation toolkit that supports modeling and simulation of cloud environments and virtualized resource provisioning. The infrastructure consisted of simulated data centers with 5 to 25 cloud nodes, each node equipped with 16 GB of RAM, 8-core processors, and 5 TB of storage. Workloads ranging from 100 to 1000 service requests were generated synthetically to simulate real-world user traffic.

The average service response time is the time elapsed between the request and the completion of the service. It

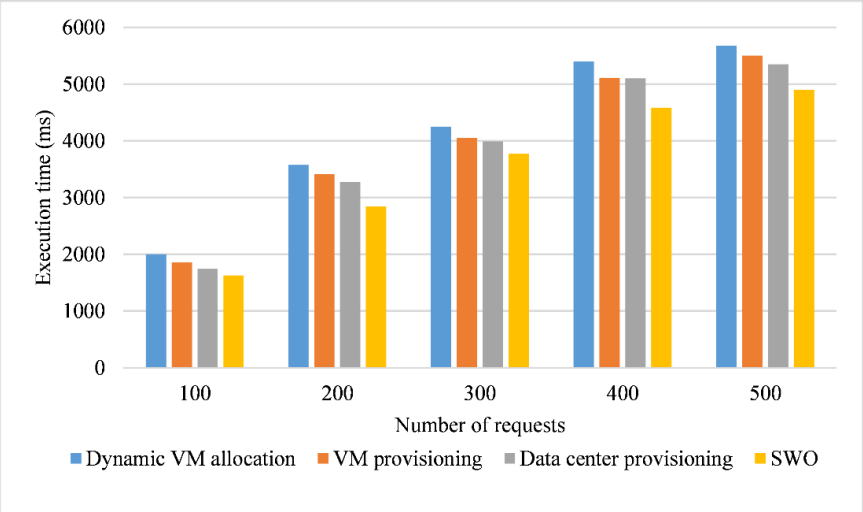

Figure 4: Service execution time comparison

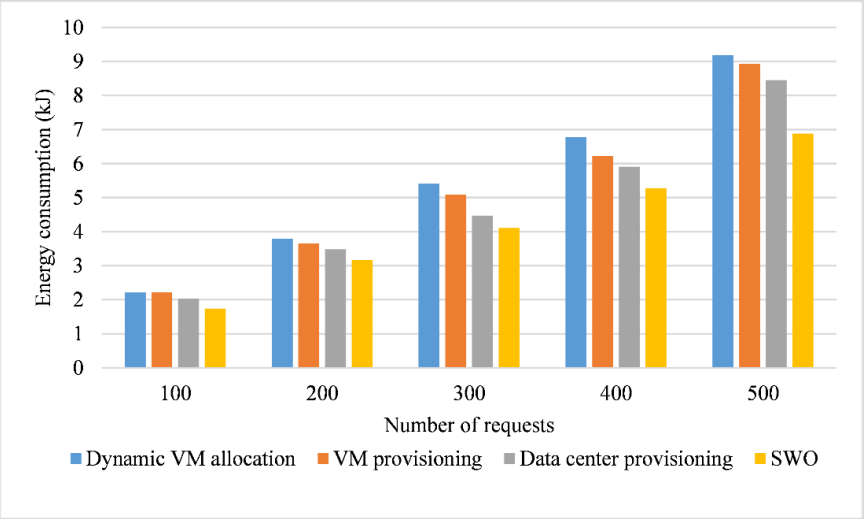

Figure 5: Energy consumption comparison

is evident from Figure 4 that the proposed method outperformed the baseline techniques at all levels of service requests. At the highest workload of 500 requests, the proposed method achieved a 24.7% ± 1.8% reduction in mean execution time, which was statistically significant ($p < 0.05$) compared to the baseline methods. It argues that this performance increase was achieved with the aid of the hierarchical resource selection strategy: the pre-selection of resources was conducted at the CMM level and refined by the GMM to select the most suitable resource based on priority levels.

Figure 4 illustrates the linear relationship between execution time and the number of service requests, demonstrating that the proposed approach is scalable. The proposed approach offers an efficient allocation process, avoiding substantial delays compared to baseline techniques, particularly for high workloads. The improved response behavior and faster execution time are likely the result of the metaheuristics of SWO, which are theoretically designed to explore the solution space systematically and prefer resource configurations with higher efficiency. Although the performance is improved, the specific influence of minimizing the search space and avoiding contention is assumed based on the algorithm design and not directly observed. Future work will involve developing special-purpose metrics to explicitly verify these factors.

Energy efficiency is the key to sustainable cloud data centers. Figure 5 illustrates the energy consumption of the various methods for variable workloads. The maximum energy consumption of the proposed approach is 6.8 kJ at 500 service requests, which is significantly lower compared to Dynamic VM Allocation (9.2 kJ), VM Provisioning (8.9 kJ), and Data Center Provisioning (8.4 kJ). The energy-saving capability of the proposed method comes from emphasizing resource allocation efficiency, thereby reducing redundant activation of underutilized servers.

The most significant energy savings achieved by the proposed approach are typically derived from the hierarchical allocation framework. For each task, the method selects the most suitable server based on

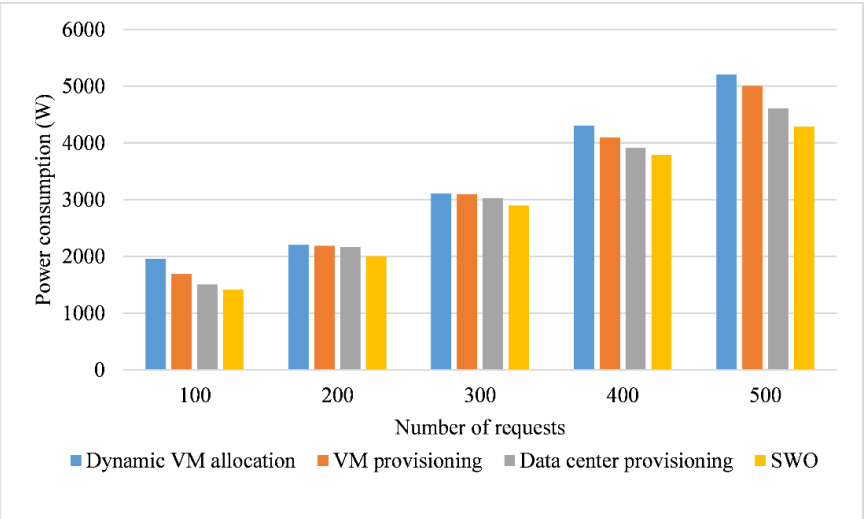

Figure 6: Execution power consumption comparison

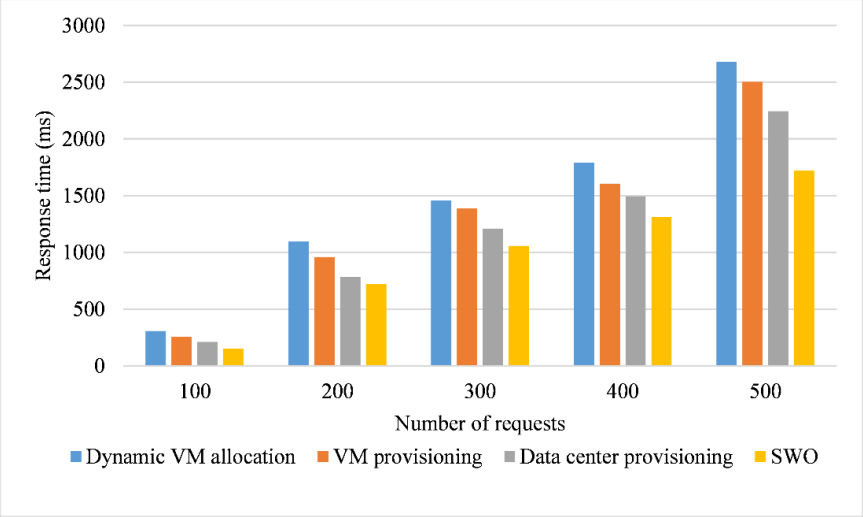

Figure 7: Response time comparison

geographical proximity and energy profiles to minimize power-hungry operations. SWO further optimizes resource usage by distributing tasks to servers operating within their optimal energy range. These results demonstrate that the proposed approach can satisfy the growing computational demands while minimizing operational costs and environmental impacts.

The power consumption is shown in Figure 6, which further verifies the efficiency of the proposed method. The power consumption for the proposed method at 500 requests was approximately 4,800 W. In contrast, for Dynamic VM Allocation, the power consumption was 5,500 W. This trend of reduction for every workload indicates the effectiveness of SWO in maintaining a perfect balance between energy efficiency and active/idle resources.

Figure 7 illustrates the response time of the proposed method compared to Dynamic VM Allocation, VM Provisioning, and Data Center Provisioning approaches for varying numbers of requests. The proposed SWO method demonstrated the lowest response time across all workload levels, indicating its efficiency in handling service requests. For instance, it can be seen that for the highest workload of 500 requests, the response time using the SWO method is significantly lower than that of the other approaches, and the latency is reduced by approximately 20% compared to Dynamic VM Allocation. Such performance could be attributed to how the hierarchical resource allocation strategy adopted in SWO optimizes resource selection and allocation, aiming to avoid bottlenecks.

Table 2: Statistical comparison of the proposed SWO-based method with baseline approaches

Metric	Compared methods	Mean difference	Std. Dev.	P-value
Service response time	SWO vs. Dynamic VM	-1.87 s	0.41 s	0.0012
Energy consumption	SWO vs. VM Provisioning	-1.63 kJ	0.38 kJ	0.0036

To validate the performance differences between our proposed method and existing strategies, we conducted paired two-tailed t-tests at a 95% confidence level for each performance metric. Table 2 reports the average improvements, standard deviations, and p-values for service response time and energy consumption across five runs.

The tests demonstrate that the predictive hierarchical resource allocation scheme based on SWO is scalable in terms of problem size. With the increase in the number of service requests, the runtime demonstrates almost linear behavior, indicating stable and manageable performance even with large workloads. Additionally, the increase in the number of cloud nodes has a moderate impact on runtime. This is because the CMM conducts the pre-selection of suitable resources, which significantly reduces the search space before the GMM applies the optimality algorithm based on the SWO. Overall, the synergistic operation of the systems ensures the responsiveness and energy efficiency of the computer systems with large-scale, dynamic clouds.

5 Discussion

The experimental results indicate that the designed two-tier SWO-based approach achieves significant improvements in service responsiveness and energy efficiency. Compared to existing methods, the designed approach achieves an average response time improvement of 25% and an energy consumption reduction of 26% under peak loads. This efficiency is attributed to the hierarchical design, which minimizes the resource candidates before the invocation of the SWO, thus minimizing the solution search space and avoiding resource contention.

Unlike others that heavily rely on mathematical programming or deep learning models, our method mitigates the high computational intensity by restricting the execution of the SWO to a pre-filtered candidate pool.

SWO outperforms its peer metaheuristics due to its adaptive global exploration and exploitation trade-off, based on the natural dynamics of hunting and mating behaviors.

Despite these strengths, the proposed method has several limitations. First, the SWO algorithm's performance can be sensitive to workload variability; sudden spikes in user demand may affect convergence quality unless it is dynamically calibrated. Second, although the SWO exhibits faster convergence than several traditional metaheuristics, it may still require tuning for real-time or low-latency applications. Third, the current implementation is tailored to homogeneous cloud architectures; its portability to federated or hybrid cloud platforms remains untested.

One notable trade-off of our solution is the incremental computational cost attributable to the SWO's iterative optimization process. Although lightweight compared to deep learning methods, it still incurs moderate runtime overhead, which may become suboptimal in ultra-time-critical applications. Nonetheless, the cost is fairly justified due to the consistent improvements in energy and QoS performance.

6 Conclusion

The presented study introduces an intelligent resource provisioning paradigm capable of enhancing energy efficiency while ensuring robust QoS in cloud infrastructure. Due to the larger environmental footprint of data centers and the growth of cloud infrastructure, the issue of unsustainable and dumb resource management is more acute than ever. To that end, we developed a two-tiered hierarchical structure that mixes the CMM and the GMM. The CMM actively filters and filters down suitable cloud resources based on the real-time parameters of the systems, namely queue length, response time, and location, and submits them to the GMM. Based on the predator-prey behavior metaheuristic algorithm, the GMM fine-tunes the selection and optimizes it according to energy efficiency. This collaborative process facilitates effective VM placement and adaptive resource provisioning. By utilizing both real-time perception of the system and intelligent optimizations, the introduced paradigm adaptively responds to variations in workload and infrastructure state. This results in reduced power consumption and improved response times across the entire cloud infrastructure.

Our results indicate a promising method for integrating nature-inspired algorithms into hierarchical management structures that can address the dual problems of QoS and energy efficiency in cloud computing. With the ongoing growth in size, cloud infrastructures will need to adopt new approaches to reduce their environmental footprint while maintaining reliable and efficient service provisioning. Future work could include determining the scalability of this approach when transitioning to an even more extensive and diverse cloud environment, as well as its adaptability to evolving technologies such as edge computing and IoT.

While the devised method is mainly applied to centralized cloud infrastructures, its architectural principles and optimization model are, at the core, extensible to the fog and edge computing paradigm. The hierarchical structure (CMM-GMM) is applicable by introducing intermediary layers that represent the fog nodes or edge devices. Additionally, the SWO can potentially optimize resource allocation among heterogeneous devices by adjusting its fitness function to consider edge-specific factors, such as latency, mobility, and battery limitations. Considering the increasing convergence of fog, cloud, and edge technologies, the proposed method provides a practical foundation for future distributed resource management systems.

Conflict of interest

The authors declare that they have no conflicts of interest.

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