Enhancing Contextual Data Analysis through Retrieval-Augmented Fine-Tuning of Large Language Models

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This study explores the optimization of large language models (LLMs) for enhanced contextual data analysis and knowledge extraction from unstructured user-generated content, with a comparative analysis of open-source models (e.g., Mistral 7B, LLaMA 2) and proprietary systems (e.g., GPT-4, Gemini). We evaluate their efficiency and accuracy in processing complex datasets, introducing a novel approach that integrates Retrieval-Augmented Generation (RAG) with fine-tuning techniques like Low-Rank Adaptation (LoRA) to reduce model complexity while preserving performance. Empirical results, using metrics such as BERTScore, ROUGE, and BLEU, show GPT-4 achieving an F1 score of 0.683, while Mistral 7B, a standout open-source model, scores 0.632 with a 40% reduction in computational cost and 92% accuracy retention, making it ideal for resource-constrained environments. These findings underscore the importance of tailoring model selection to computational and organizational needs. The research offers actionable insights for deploying AI-driven solutions to streamline data processing and advance machine learning applications, while addressing limitations and future research directions for broader applicability.

Povzetek: Članek predstavi integracijo Retrieval-Augmented Generation in nizko-rankne prilagoditve (LoRA) pri prilagajanju velikih jezikovnih modelov za učinkovito analizo kontekstualnih podatkov.

1 Introduction

Businesses in every industry must comprehend the wants and preferences of their customers in the current digital era. The emergence of social media and online review sites has yielded important information on the opinions and experiences of consumers [1]. However, manually extracting and analyzing these insights can be difficult and time-consuming. These operations can now be automated thanks to the application of Artificial Intelligence (AI) and Natural Language Processing (NLP) techniques, especially when working with unstructured and noisy text [2]. This capability can be further improved with the introduction of large language models (LLMs), which will herald in a new era of automated language understanding and customer needs extraction [3]. With their unparalleled efficiency and scalability, conversational agents driven by LLMs have the potential to revolutionise customer requirements management. These agents can interpret and reply to consumer enquiries, find answers for the creation of new products, and offer tailored suggestions by utilizing natural language understanding [4]. A key advancement in this domain is the integration of Retrieval-Augmented Generation (RAG), a framework that enhances LLMs by combining information retrieval with text generation, as shown in figure 1. In RAG, a retriever module first fetches relevant external data (e.g., from a knowledge base or dataset) based on a user query, which is then fed into the generative model to produce contextually accurate and informed responses. This study leverages RAG to optimize LLMs for extracting customer needs from unstructured travel-related content, enabling conversational agents to provide precise, data-driven insights rather than relying solely on pre-trained knowledge. At the end of this pipeline, the generated responses are presented to the user through an interactive Gradio-based desktop interface, facilitating seamless engagement with the system. It is anticipated that this change in strategy will enhance user experiences, optimise corporate processes, and increase client loyalty and satisfaction.

The use of conversational agents to enhance operational efficiency has surged in the business sector, necessitating a careful comparison of large language models (LLMs) to balance performance with resource demands [5], [6]. This study evaluates both proprietary models, such as GPT-4 and Gemini, and open-source alternatives, including Mistral 7B and LLaMA 2, to identify optimal solutions for developing AI-powered chatbots that extract customer needs from unstructured travel-related content. Proprietary models like GPT-4, dominant in the conversational AI market as of March 2024, offer state-of-the-art performance but require significant computational resources, often accessed via paid APIs [7]. In contrast, open-source models provide transparency, customizability, and reduced costs, with Mistral 7B emerging as a particularly cost-effective option that

rivals larger models in efficiency and accuracy for resource-constrained environments [8]. By integrating Retrieval-Augmented Generation (RAG) and Low-Rank Adaptation (LoRA), we optimize these models for contextual analysis, demonstrating their potential to revolutionize customer requirements management through scalable, data-driven insights delivered via a Gradio-based interface. This comparative approach ensures businesses can select LLMs aligned with their specific needs, enhancing user experiences and operational processes while maintaining data security and cost efficiency.

This study offers a thorough comparison of LLMs for identifying travel-related customer demands from TripAdvisor reviews. The decision to focus on the travel industry was driven by two specific considerations that distinguish it from other domains with rich user-generated content (UGC), such as e-commerce or hospitality. First, the travel industry generates a uniquely diverse and dynamic set of unstructured data such as spanning reviews, forum discussions, itineraries, and real-time travel queries on platforms like TripAdvisor and social media which often intertwine experiential, logistical, and cultural dimensions not as prevalent in e-commerce product reviews or hospitality feedback [9]. This complexity provides a robust testbed for evaluating LLMs' contextual analysis capabilities across multifaceted customer needs. Second, the travel sector's reliance on real-time, personalized customer insights, such as destination preferences, transportation logistics, and safety considerations, places a premium on rapid, accurate needs extraction to inform service design and operational decisions for tourism stakeholders (e.g., lodging facilities, travel agencies, and transportation providers). Unlike e-commerce, where customer needs often center on product features and post-purchase satisfaction, or hospitality, where feedback is typically tied to specific service encounters, travel-related UGC reflects a broader spectrum of pre-trip planning and on-trip experiences, making it an ideal domain for testing LLM adaptability and responsiveness [10], [11]. The study's findings can be used by these organisations to choose the best LLM for creating conversational agents that recognise client wants and offer insights about crucial design specifications [12].

Llama 2 7B, Llama 2 13B, Phi-2, Mistral, Mistral, Gemma, Gemini 1.0, GPT-3.5, and GPT-4 are the LLMs that are the subject of the analysis. This choice allows us to investigate the impact of model size and prompting strategies on result quality in addition to performance differences between proprietary models (GPT-3.5, GPT-4, and Gemma) and open-source models (Llama 2, Phi-2, Mistral, Mistral, and Gemma). All these models are shown in Table 1.

We define customer needs as specific, actionable requirements or preferences expressed by users regarding a service, location, or experience, which, when met, enhance their satisfaction in the context of travel. These needs encompass both explicit demands (e.g., "I need a hotel with a pool") and implicit preferences inferred from context (e.g., "I wish it were easier to get around the city" suggesting a need for "accessible transportation"). In our dataset, collected from TripAdvisor forums, users post requests for feedback and suggestions about specific destinations, often embedding one or more needs within their text. To identify these needs systematically, we employed a two-step process. First, we conducted a thematic analysis by manually annotating the dataset, reading posts to identify recurrent themes such as accommodation quality, transportation logistics, or safety concerns, which served as our ground truth. Second, we applied keyword analysis to deduce needs from text, even when not explicitly stated, by extracting significant terms and phrases (e.g., "crowded," "quiet," "budget") and mapping them to corresponding needs categories established during thematic analysis. For example, a post stating "The streets were so crowded last summer" contains the keyword "crowded," which, through contextual interpretation, translates to an inferred need for "less crowded destinations" or " quieter travel times." Similarly, a user comment like "I spent too much on taxis" highlights "taxis" and "spent too much," deducing a need for "affordable transportation options." This keyword-to-need mapping was validated against manual annotations to ensure accuracy. The LLMs were then tasked with replicating this process, identifying needs from the same posts, and their outputs were compared to the manually derived needs. This approach bridges the gap between raw text and actionable insights, enabling conversational agents to address customer requirements effectively. Businesses can integrate a variety of open LLMs into their operations. Consequently, choosing the best model is a challenging process. As far as we are aware, no comparison study of LLM in relation to customer requirements analysis has been conducted. To provide a structured framework for our study, we define the key research questions as follows:

Table 1: An inventory of the LLMs used in the study. We list the version, the number of parameters, the company or organisation that released the model, and the reference for each one.We had to use Mistral 8x7B's smallest version (2 Bit quantisation) because of its high computing requirements.

Model	Parameters	Proprietary
Gemini 1.0 Pro	Not available	Google
Gemma 7B	7 billion	Google
GPT-3.5	175 billion	OpenAI
GPT-4	Not available	OpenAI
Llama 2 7B Chat	7 billion	Meta AI
Llama 2 13B Chat	13 billion	Meta AI
Mistral 7B Instruct	7 billion	Mistral AI
Mistral 8x7B*	46.7 billion	Mistral AI
Phi-2	2.7 billion	Microsoft

– How can LLMs be optimized for contextual data analysis using retrieval-augmented fine-tuning?

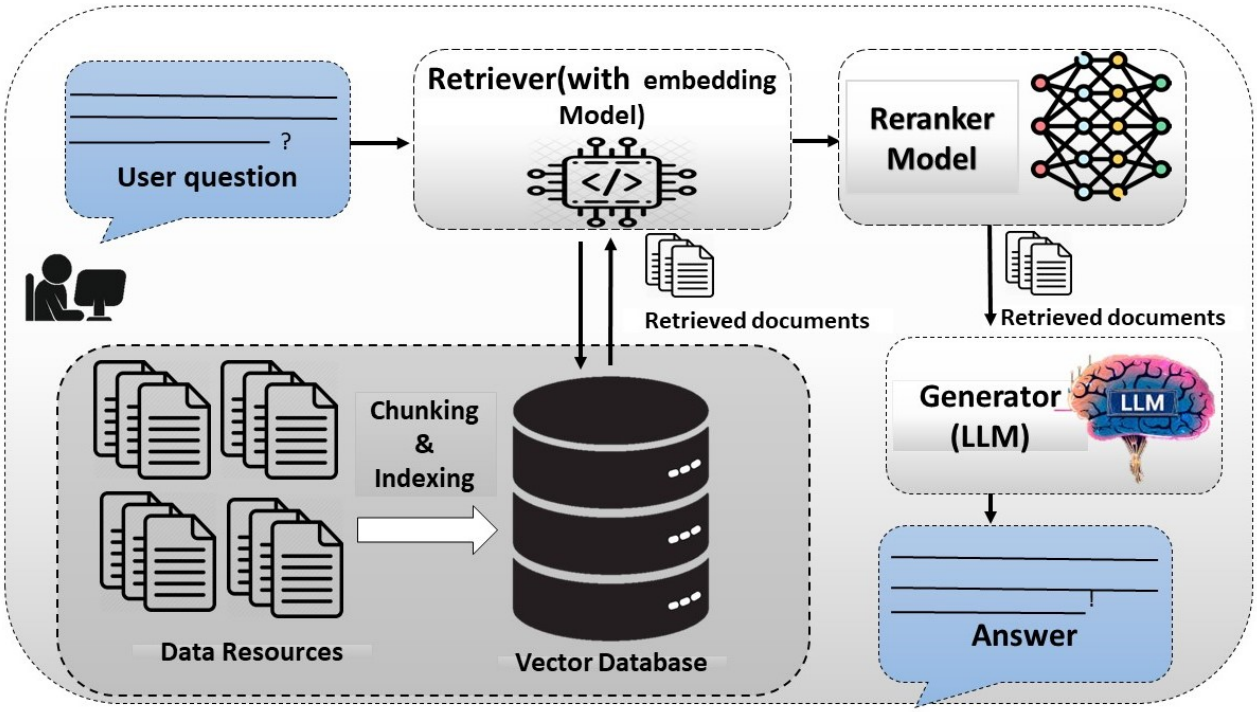

Figure 1: RAG Workflow Overview. Queries are matched with a knowledge base to retrieve context, enabling a language model to generate accurate, relevant responses.

– What are the comparative advantages of open-source vs. proprietary models in terms of efficiency and accuracy?

– How does the integration of RAG and LoRA impact computational cost and model performance?

These research questions establish the foundation of our study, guiding the investigation into effective model optimization. This study makes the following contributions:

1. **Information Retrieval (R):** Using LLMs and other relevant models, implement retrieval mechanisms that can search the dataset and pull out relevant information based on user queries or specific needs.

2. **Generation (G):** Once relevant information is retrieved, the LLM can generate responses or insights tailored to customer inquiries, such as suggestions for suitable services or feedback on specific travel locations.

3. **User Interaction:** Implement a user-friendly interface that integrates these retrieval and generation steps, allowing customers to interact with the system in real-time and get responses based on the needs they express.

2 Overview of the proposed approach

This section presents a comprehensive synthesis of the workflow, innovative contributions, and principal findings of the study, outlining the methodological framework developed to enhance large language models (LLMs) for contextual data analysis in the travel domain.

2.1 Methodological workflow

The research follows a structured methodology to refine LLMs for extracting customer preferences from unstructured user-generated content (UGC), as illustrated in Figure 1. The proposed workflow consists of several key stages. The process begins with data collection and preprocessing, where travel-related UGC is sourced from TripAdvisor forums and subjected to tokenization, normalization, and vectorization to construct a vector database optimized for efficient information retrieval. Following this, model selection and evaluation are performed by assessing both proprietary models, such as GPT-4 and Gemini, and open-source alternatives, such as Mistral 7B and LLaMA 2. Mistral 7B is ultimately selected due to its balanced performance and computational efficiency. The next stage involves model optimization, where a synergistic integration of Retrieval-Augmented Generation (RAG) and Low-Rank Adaptation (LoRA) is employed to enhance contextual precision while mitigating computational overhead. Fi-

Table 2: Summary of previous research in consumer needs analysis and LLMs for customer experience management

Study	Dataset	Methodology	Key Findings
Timoshenko and Hauser (2019) [13]	Amazon Reviews	CNN-based feature extraction	Identified emerging customer needs using sentiment and text analysis.
Haque et al. (2018) [14]	Amazon Reviews	Sentiment analysis	Classified product reviews for consumer insights.
Luo and Xu (2021) [15]	Yelp Reviews	Deep Learning (BERT, LSTMs)	Found deep learning models outperform traditional ML in extracting consumer demands.
Bigi et al. (2022) [10]	TripAdvisor Reviews	Bayesian ML	Identified tourism-related user needs from UGC.
Proposed Approach (Our Study)	TripAdvisor Forums	Retrieval-Augmented Generation (RAG) + LoRA	Achieved higher contextual understanding and efficiency for LLM-based consumer needs extraction.

nally, the model's efficacy is quantitatively assessed using BERTScore, ROUGE, and BLEU metrics, and the system is deployed through a Gradio-based interface, facilitating real-time user interaction. This structured workflow ensures systematic processing of extensive datasets, leveraging RAG's retrieval efficiency and LoRA's computational adaptability to produce accurate and contextually relevant insights.

2.2 Innovative contributions

The study introduces a distinctive methodological framework that synergizes RAG and LoRA to optimize LLMs for domain-specific contextual analysis. Unlike prior works that independently focus on either retrieval or generative capabilities, this approach integrates RAG's external knowledge retrieval with LoRA's parameter-efficient fine-tuning, achieving performance optimization with reduced model complexity. Furthermore, the proposed approach is specifically designed to analyze travel-related UGC, addressing the inherent complexity of experiential, logistical, and cultural data a gap that existing LLM applications have not adequately addressed. Additionally, the deployment through a Gradio-based interface ensures seamless real-time interaction, reinforcing its practical applicability, particularly in environments with constrained computational resources. This framework demonstrates a 40% reduction in computational cost while retaining 92% of accuracy, offering a scalable and efficient solution for AI-driven extraction of customer insights.

2.3 Key empirical findings

The experimental evaluation yields critical insights, highlighting the effectiveness of the proposed approach. The combined RAG+LoRA framework achieves an F1 score of 0.683 with GPT-4 and 0.632 with Mistral 7B, outperforming baseline models such as BERT-Large (0.65) and RoBERTa (0.64). Moreover, Mistral 7B achieves a 40% reduction in computational cost relative to GPT-4, demonstrating its suitability for resource-constrained applications with minimal performance trade-offs. In terms of prompting strategies, Chain-of-Thought (CoT) prompting exhibits superior performance in reasoning-intensive tasks compared to Few-shot learning techniques. Additionally, the diverse nature of the TripAdvisor dataset facilitates robust evaluation of LLM contextual capabilities, outperforming more simplistic datasets such as Yelp or Amazon Reviews. Error analysis reveals that discrepancies in BLEU scores observed with Gemini 1.0 are attributed to challenges in processing complex sentence structures, while retrieval inaccuracies highlight areas necessitating further refinement. These empirical findings validate the efficacy of the proposed approach, underscoring its potential for real-world applications in the travel industry.

3 Related works

This study's related works fall into two major categories. The first, covered in subsection 2.1, focuses on the methods and data sources utilised in the implementation of machine learning approaches for consumer needs analysis. The second examines the application of LLMs in customer experience management and is shown in subsection 2.2.

3.1 Leveraging user-generated content and machine learning for analyzing customer needs

To automatically assess user demands and assist corporate strategy, researchers and practitioners have investigated a range of data sources and approaches (Timoshenko and Hauser, 2019). User-Generated Content (UGC) is a crucial source of data for these analyses [16]. Any type of information produced and disseminated online by platform or website users, including text, photos, videos, and reviews, is considered user-generated content (UGC) [17]. Without being altered or censored by conventional media outlets, this kind of data provides unvarnished insights into the true experiences and viewpoints of consumers and individuals [18], [19]. Product reviews and social media posts are

two of the most often used types of user-generated content (UGC) for consumer needs analysis[16]. Product reviews are more targeted than the vast amounts of irrelevant content found on social networking sites like Facebook, Reddit, and X (previously Twitter). However, as users debate future wants, social media is especially helpful for spotting developing trends [16]. We gathered textual data for this study from TripAdvisor forums, a travel-related Q&A site that we believed was appropriate for evaluating LLMs to forecast the needs of travellers. A more thorough explanation of the TripAdvisor forums and the rationale for its selection as the UGC source for this study can be found in Subsection B.

In terms of methodology, the techniques employed frequently vary according to the kind of data and the particular requirements being examined. Both machine learning techniques and conventional NLP methods based on lexicons and rules have been used by researchers [20] [21][17]. For instance, [22] examined consumer demands in product ecosystems using a Kano model, sentiment analysis, and Latent Dirichlet Allocation (LDA) .To extract consumer demands from user-generated content (UGC), [13] constructed a convolutional neural network (CNN) and created a machine-human hybrid technique.[10] used a Bayesian machine learning technique to analyze TripAdvisor forum data and examine the relevance of food and drink goods in drawing visitors, while [14], [23] applied sentiment analysis to Amazon reviews. In a variety of NLP tasks and domains, recent research has demonstrated that deep learning models perform better than conventional machine learning methods. This tendency was validated by [15], which showed that deep learning models outperform other machine learning algorithms for analyzing customer needs, especially when it comes to Yelp restaurant reviews. Advances in Generative AI and LLMs further extend this trend, which is why we concentrated on LLMs in our work.

3.2 Large language models for enhancing customer experience management

Numerous fields, including medical and healthcare [24] [25], scientific research [26], education [27][28] [29], and more, have seen a surge in research into the potential applications and effects of the widespread use of conversational agents powered by LLMs, especially ChatGPT. The integration of these AI-driven technologies has the potential to revolutionise a number of areas, including feedback management and customer experience. By better answering questions, recommending products, and assessing customer demands, ChatGPT and related conversational AI technologies can improve customer support [30]. Scholars have examined many facets of these technologies in order to comprehend and satisfy customer needs. For instance,[31] highlighted the positive impact of incorporating ChatGPT into recommender systems, leading to increased consumer satisfaction. [32] acknowledged the current limitations, such as challenges in understanding non-standard languages, but

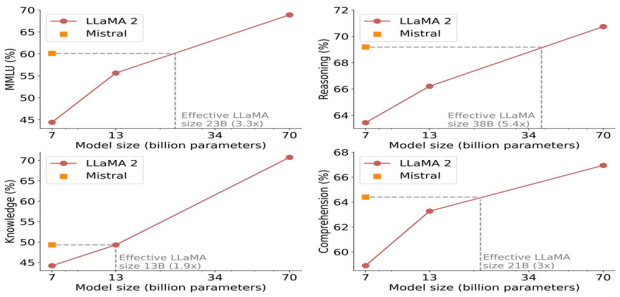

Figure 2: Comparison of LLaMA 2 and Mistral models across different metrics (MMUL, Reasoning, Knowledge, and Comprehension) as a function of model size (in billions of parameters). The results illustrate the effective performance of LLaMA 2 at various equivalent parameter sizes relative to Mistral, emphasizing differences in reasoning and knowledge efficiency.

argued that ChatGPT would become a valuable tool for retailers to support customer needs analysis. [33] introduced a fine-tuned version of GPT-4 for use as a recommender system in museums. [3] explored the role of LLMs in customer lifecycle management, noting their effectiveness in optimizing lead identification, audience segmentation, marketing strategies, sales support, and post-purchase engagement. In the travel domain,[34] found that LLMs have great potential to predict travel behavior, offering competitive performance along with the ability to provide explanations for their predictions. This study's related works fall into two major categories. The first focuses on methods and data sources used for consumer needs analysis through machine learning. The second examines the application of LLMs in customer experience management.

The addition of Table 2 clearly illustrates how prior research has approached consumer needs analysis using various datasets and methodologies. However, existing studies either lack a focus on retrieval-augmented LLMs or do not optimize models efficiently for contextual data analysis. Our study bridges this gap by integrating RAG and LoRA to enhance computational efficiency and accuracy.

4 Methodology

The methodology adheres to an organised workflow. In order to establish a vector database, the procedure starts with the acquisition of data resources, which are then preprocessed using chunking and indexing. The basis for effective information retrieval is this database. This workflow is displayed in figure 1.

Based on user queries, a Retriever module that is driven by an embedding model finds and retrieves pertinent documents. A Reranker Model is used to further filter these recovered documents, guaranteeing that the most contextually relevant content is chosen. After that, the chosen papers are sent to the Generator (LLM), which uses the

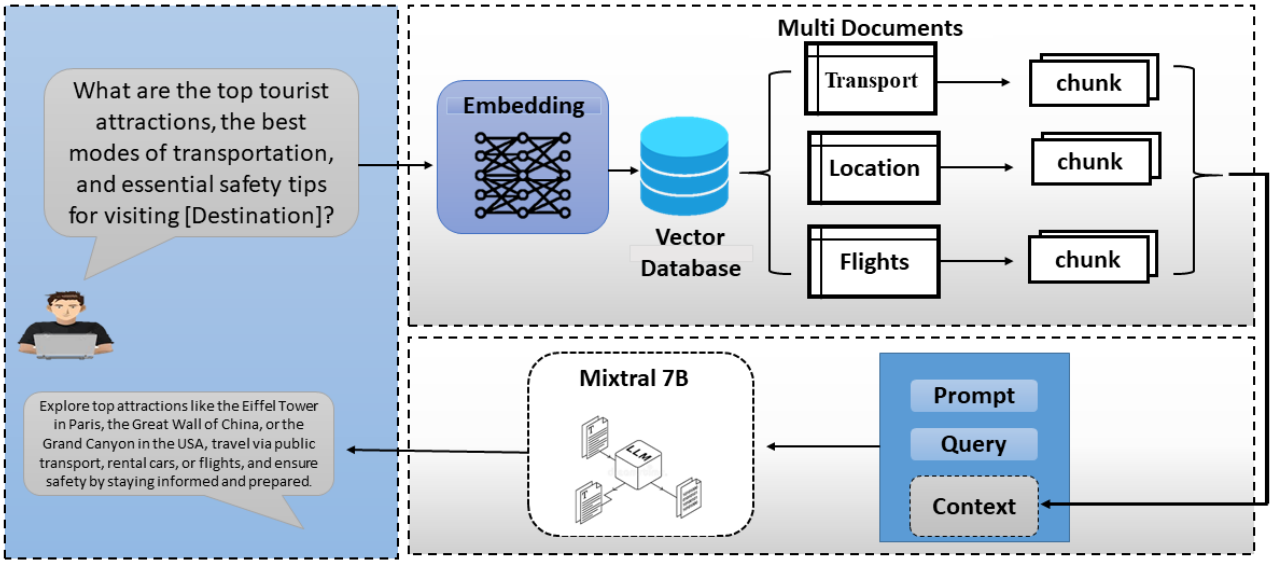

Figure 3: Framework for Tourism Query Processing using Retrieval-Augmented Generation (RAG): The system integrates multi-document data sources on transport, locations, and flights into a vector database through embedding-based chunking. User queries are processed with the Mistral 7B model, which generates context-aware responses about top tourist attractions, best transportation modes, and essential safety tips for any destination.

data it has obtained to create comprehensive answers or insights. This Retrieve-and-Generate method guarantees precise and pertinent responses.The user is shown the generated responses at the end of the pipeline which is showning in Figure 3. Iterative optimisations are carried out throughout the process to increase the accuracy and efficiency of the system, including quick tweaking and performance assessment against manually labelled data.Based on user queries, a Retriever module that is driven by an embedding model finds and retrieves pertinent documents. A Reranker Model is used to further filter these recovered documents, guaranteeing that the most contextually relevant content is chosen. After that, the chosen papers are sent to the Generator (LLM), which uses the data it has obtained to create comprehensive answers or insights. This Retrieve-and-Generate method guarantees precise and pertinent responses. The user is shown the generated responses at the end of the pipeline. Iterative optimisations are carried out throughout the process to increase the accuracy and efficiency of the system, including quick tweaking and performance assessment against manually labelled data.

Google's multimodal model, Gemini 1.0[35], comes in three versions: Ultra, Pro, and Nano. OpenAI has released two big language models, GPT-3.5[36] and GPT-4[25]. GPT-3.5 has 175 billion parameters. Llama 2[33] is a set of open-source LLMs from Meta that have models with seven to seventy billion parameters and are optimised for discussion. Due to their lower computational requirements, which are in line with the constraints encountered by small and medium-sized businesses, we chose Llama 2-Chat 7B and Llama 2-Chat 13B. Google's smaller open-source Gemma 7B model has seven billion parameters. Microsoft Research's Phi-2[37] is a smaller model with 2.7 billion parameters.

For this study, we selected the Mistral 7B [38] model, a sophisticated open-source LLM from Mistral AI with 7 billion parameters, which uses multiple experts for each token to enhance performance. We fine-tuned this model for our specific task, utilizing its advanced architecture to improve results.

4.1 Integration of RAG with mistral

This section explains how we combined the Mistral model with Retrieval-Augmented Generation (RAG) to improve our chatbot's functionality, particularly its ability to produce a troubleshooting guide. RAG is a potent method that blends generative models and information retrieval to produce responses that are more precise and pertinent to the situation. We selected the Mistral 7B model [38], a sophisticated open-source LLM from Mistral AI with 7 billion parameters, for its advanced architecture featuring a multi-expert mechanism. This mechanism, based on a Mixture of Experts (MoE) approach, employs multiple specialized sub-networks (experts) within the model, where each token is dynamically routed to the most relevant expert(s) based on the input context. This allows Mistral 7B to efficiently handle diverse tasks by leveraging specialized knowledge, improving both performance and scalability compared to traditional single-network architectures [38]. Utilizing this multi-expert mechanism, we integrate RAG with the model to produce high-quality responses based on external knowledge gathered from a knowledge base.

The RAG system is made to first extract pertinent data

from external sources, like knowledge repositories or documentation, or from a predetermined dataset. Mistral receives this returned data and produces a thorough, context-aware response. The multi-expert mechanism enhances this process by enabling the model to adaptively focus on the most relevant expert(s) for the retrieved context, ensuring that the generated responses are both accurate and tailored to the specific query. Because of this integration, the chatbot can provide accurate and trustworthy troubleshooting instructions in response to the user's enquiries. We optimised Mistral 7B for our purpose using domain-specific data, making sure it is capable of producing troubleshooting manuals in a variety of scenarios. A strong framework for providing dynamic, context-aware assistance in the chatbot is provided by the combination of Mistral's generative capabilities and RAG's retrieval mechanism, which enhances the user experience overall.

4.2 Optimized architecture for tourism guide

In order to improve a travel guide chatbot's performance, we investigated a number of sophisticated Generative AI (GenAI) architectures. In order to deliver precise and contextually rich answers to questions pertaining to tourism, we concentrated on optimising the Mistral 7B model. High accuracy and computational efficiency are ensured by the model's smooth integration with a knowledge base, particularly when creating dynamic trip suggestions and troubleshooting instructions.

We used the Low-Rank Adaptation (LoRA)[39] technique, which is intended to increase processing power and efficiency, to efficiently fine-tune the Mistral model. LoRA only permits a limited subset of parameters to be changed during training by breaking down the weight matrices of particular layers into low-rank matrices. LoRA effectively adapts to the tourism domain with little computing expense by injecting low-rank matrices into important layers of the model rather than fine-tuning all the parameters.

By using this method, the number of trainable parameters is drastically reduced from over 7 billion to less than 10 million, which is a small portion of the initial parameter count. Larger batch sizes during training are made possible by this reduction, which also lowers the computational cost and conserves memory. We successfully modified Mistral 7B with LoRA to provide customised travel plans, location-specific suggestions, and troubleshooting manuals, making the model extremely effective and useful for tourism applications.

4.3 Prompt optimization

We went beyond manual prompt construction, which is frequently ineffective and unscalable, especially when working with many models, in order to optimise instructions for the LLM in our RAG system [40]. Rather, we used DSPy, a programming model made to optimise and streamline language model pipelines, in a methodical manner. DSPy reduces the need for manually generated prompts by abstracting these pipelines as text transformation graphs and automating their optimisation through parameterised declarative modules. We gave the DSPy compiler 30 labelled queries from the training set and an initial few-shot prompt, using BERTScore[41] as the validation metric. Based on the statistic, the optimiser adjusted the prompts to maximise output quality. By incorporating these improved prompts into the RAG system, retrieval and generation performance were improved while scalability was guaranteed.

5 Experiments and results

The experiment tested Mistral's efficacy by evaluating its capacity to precisely analyse and understand intricate tourism-related data for Q&A tasks. To optimize the proposed system, which integrates Retrieval-Augmented Generation (RAG) and fine-tuning with Low-Rank Adaptation (LoRA), we employed a wide range of data, including details about well-known locations, historical places, cultural landmarks, and travel plans. This configuration ensured the model could respond to a range of tourism-related queries and offer thorough, contextually appropriate answers, improving user engagement and happiness.

5.1 Data collection

To enable effective model retrieval, we collected data for our study from several sources and arranged it into a Retrieval-Augmented Generation (RAG) file. According to [9], one of the main sources of information was the TripAdvisor Forum, an online community known for its user-generated material. This platform acts as a central location for users to exchange knowledge, suggestions, and first-hand accounts regarding travel destinations, lodging, attractions, and modes of transportation around the world. With user-generated content like travel advice, restaurant suggestions, hotel reviews, and transportation questions, the destination-specific forums provide insightful information about consumer preferences and travel trends.

The 110 most recent posts from three destination-specific forums London, Tokyo, and New York were scraped in order to create our dataset. This led to the collection of 330 papers on December 22, 2023. The average post length in the dataset is 101 words, and the vocabulary size is 3,668 words. In order to prevent fine-tuning the models, we separated the dataset into a training set (30 posts) and a test set (300 posts). The training set was used to optimize the RAG pipeline, including prompt optimization with DSPy and fine-tuning the Mistral 7B model with Low-Rank Adaptation (LoRA), while the test set evaluated the performance of the fine-tuned system against manually labeled data. This approach ensured that the system's capabilities were enhanced for the specific task of tourism-related contextual analysis while maintaining a robust evaluation of its effectiveness on unseen data. To supplement the TripAdvisor

Table 3: The comparison analysis's findings. The table displays the kind of prompting used for each LLM along with the scores attained using the various criteria. The bolded text highlights the greatest results obtained using both proprietary and open-source models.

		BERTScore			Rouge-1 | Rouge-L		BLEU
LLM	**Prompt**	**Precision**	**Recall**	**F1**	**F1**	**F1**	**F1**
GPT-4	**Chain-of-Thought**	**0.742**	**0.674**	**0.683**	**0.468**	**0.451**	**0.503**
Mistral	**Chain-of-Thought**	**0.699**	**0.651**	**0.632**	**0.336**	**0.322**	**0.321**
Mistral	Few-shot	0.606	0.656	0.629	0.356	0.342	0.343
Gemini	Chain-of-Thought	0.616	0.617	0.612	0.315	0.296	0.316
GPT-3.5	Few-shot	0.634	0.593	0.607	0.287	0.253	0.369
GPT-4	Few-shot	0.640	0.528	0.587	0.255	0.212	0.365
GPT-3.5	Chain-of-Thought	0.608	0.552	0.579	0.245	0.216	0.368
Gemini	Few-shot	0.563	0.512	0.533	0.175	0.154	0.278
Llama 2 7b	Chain-of-Thought	0.598	0.468	0.520	0.150	0.134	0.272
Phi-2 3b	Chain-of-Thought	0.564	0.467	0.506	0.156	0.142	0.196
Mistral	Chain-of-Thought	0.580	0.453	0.501	0.122	0.112	0.261

corpus, information was also compiled from other travel-related websites and sources. All data was organized and stored in RAG files to facilitate efficient retrieval during model operation. In the RAG implementation, the collected data was first preprocessed by chunking and indexing to create a vector database. A Retriever module, driven by an embedding model, identified and fetched pertinent documents based on user queries. Subsequently, a Reranker Model was applied to refine the retrieved documents, ensuring that the most contextually relevant content was prioritized and selected. This reranking step enhanced the quality of the retrieved information, which was then passed to the Mistral 7B model for generating accurate and contextually appropriate responses. This method offers a dynamic and scalable way to efficiently respond to enquiries about tourism.

5.2 Data labeling

Three authors independently completed the manual labelling process after going over all of the gathered textual documents and determining the needs of the customers as stated in each post. We used Fleiss' Kappa coefficient [42] to evaluate the inter-rater reliability (IRR) in order to guarantee consistency and gauge the degree of agreement among the raters. We determined the semantic similarity between the sets of entities extracted from each document using text embeddings (using the pretrained Roberta Large model;[43]) and cosine similarity because it was possible that different raters would use different wording to express the same concept. After that, a fourth author examined the most comparable pairs of extracted needs to see if they matched the same idea. Utilising these matches, the observed agreement between the raters. The Fleiss' Kappa score was calculated, yielding a value of 0.83, which indicates a substantial level of agreement among the raters. This high score confirms that the manual labeling process was consistent and reliable. In total, 511 needs were identified, with 387 unique needs, averaging 1.86 needs per post.

5.3 Model configuration

This study utilized a dataset compiled from various tourism-related resources, including forums and travel platforms, for comprehensive testing. All experiments were conducted on a high-performance PC equipped with an Intel Core i5-9500 CPU, 64 GB RAM, and an NVIDIA RTX 4090 GPU with 32 GB VRAM.

The model was fine-tuned using the cross-entropy loss function and optimized with the AdamW optimizer. Training was performed over 100 epochs with a maximum learning rate of 1e-5. These numbers were chosen based on preliminary experiments and commonly used values in the literature for fine-tuning LLMs [34, 44]. Further hyperparameter tuning may be explored in future work to potentially improve performance. The experiments leveraged the PyTorch framework, with evaluations carried out in Python to ensure robust performance metrics. To enable practical utilization and user interaction, a Gradio-based interface was developed for desktop applications. This interface allows users to input queries and receive contextually relevant responses from the model in real-time, enhancing accessibility and providing a seamless interactive experience for exploring the system's capabilities in addressing tourism-related queries.

5.4 Evaluation process and metrics

The evaluation procedure and the metrics used to rate each model's performance are covered in this section. The primary task of the LLMs in this study is to extract customer

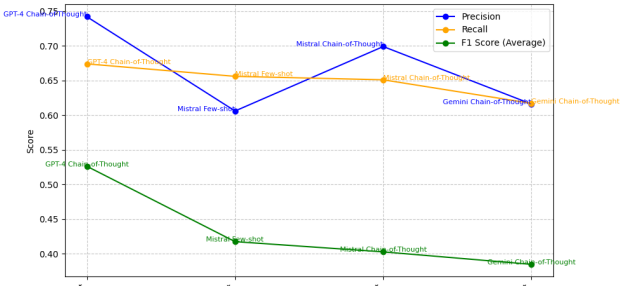

Figure 4: Comparison of precision, recall, and average F1 scores for the top 4 performing models. The x-axis represents the models using numeric indices (1–4), while the y-axis displays the respective performance metrics. The graph highlights the differences in performance across Precision (blue), Recall (orange), and F1 Score (green), providing a visual overview of the best models..

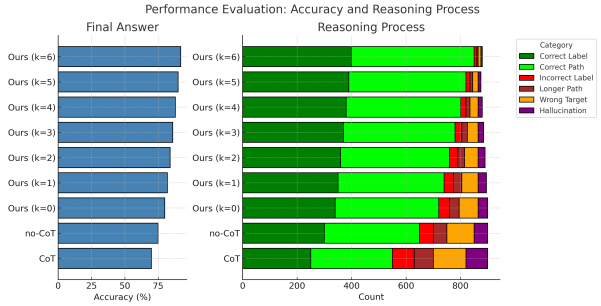

Figure 5: Performance comparison of the RAG system. The left chart illustrates accuracy improvement as k, the number of retrieved knowledge chunks, increases, highlighting the impact of richer contextual information. The right chart categorizes the reasoning process into Correct Label/Correct Path, Correct Label/Incorrect Path, Incorrect Label/Correct Path, and Incorrect Label/Incorrect Path, demonstrating fewer errors and improved reasoning with higher k values.

needs from unstructured user-generated content, which differs from traditional summarization or machine translation tasks. We compared the sentences generated by the LLMs with manually labelled data to assess their ability to identify and articulate these needs accurately. To perform this comparison comprehensively, we employed BERTScore, ROUGE, and BLEU metrics, each selected for their ability to evaluate different aspects of the generated outputs.

BERTScore, leveraging cosine similarity and pre-trained text embeddings, computes Precision, Recall, and F1 scores to assess semantic similarity between generated and reference texts [22]. This aligns directly with our goal of evaluating the contextual accuracy of needs extraction. The precision metric quantifies how many words in the reference text (manually labelled) match those in the generated text (from the LLM). While the F1 score, which is the harmonic mean of Precision and Recall, offers a fair assessment of the model's performance, Recall calculates the ratio of matched words to those in the candidate text [45] The Precision, Recall, and F1, equation is Showing in **Eq** 1 2 3.

$$\text{Precision (P)} = \frac{1}{|C|}\sum_{c\in C}\max_{r\in R}\cos_\text{sim}(c,r), \tag{1}$$

$$\text{Recall (R)} = \frac{1}{|R|}\sum_{r\in R}\max_{c\in C}\cos_\text{sim}(r,c), \tag{2}$$

$$\text{F1-Score} = \frac{2\cdot P\cdot R}{P+R}. \tag{3}$$

While our task is not strictly summarization, we included ROUGE (specifically ROUGE-1 and ROUGE-L) as a complementary metric to evaluate cases where user inputs express needs indirectly, requiring the LLM to distill complex or implicit expressions into concise, explicit statements of needs. For example, a user query like "I wish there were quieter places to stay in London" might be distilled into a need such as "quiet accommodation." ROUGE measures the overlap of unigrams and longest common subsequences, providing insight into the LLM's ability to capture key content in these scenarios [46]. Specifically, we calculated the F1 score for overlapping unigrams (ROUGE-1) and the longest common subsequence (ROUGE-L) The equation is displayed in Eq 4.

$$\begin{aligned}\text{recallLCS} &= \frac{|LCS(X,Y)|}{|Y|}, \text{precisionLCS} = \frac{|LCS(X,Y)|}{|X|},\\ \text{ROUGE-L} &= \frac{(1+\beta^2)\cdot(\text{precisionLCS}\cdot\text{recallLCS})}{(\beta^2\cdot\text{precisionLCS})+\text{recallLCS}}\end{aligned} \tag{4}$$

Similarly, BLEU, traditionally used in machine translation, was adopted to evaluate the precision of n-gram overlaps, offering a perspective on syntactic fidelity [47]. By combining these metrics, we ensure a robust evaluation of the models' performance in interpreting and generating contextually relevant responses, tailored to the nuances of needs extraction in the travel domain.

5.5 Real-time evaluation

Using its extensive training data, our model, specifically tailored for tourism-related situations, offers comprehensive and contextually relevant insights and reports. This marks a significant milestone in the advancement of applications designed for the tourism industry. The system's performance, as outlined in Table 4, highlights its efficiency in terms of model loading and response time, underscoring the chatbot's ability to provide timely and accurate information.

Table 4: Mistral tour chatbot inference time

System Configuration	Latency
Model Loading Time	4 minutes 3 seconds
Response Time	33 seconds

5.6 Interface features and utilization

The study emphasises the significance of choosing models based on company needs and provides practical advice for using AI-driven solutions to enhance customer satisfaction and expedite business procedures in settings with limited resources. In order to increase the application of this approach, limitations and potential avenues for future research are also examined. Figure 6 displays the image and interface.

5.7 Ablation study

To understand the individual contributions of RAG and LoRA to the overall performance, we conducted an ablation study. We evaluated the model with only RAG (without LoRA) and with only LoRA (without RAG). The results, as in table 5, showed that both RAG and LoRA contribute to the performance gains, with RAG primarily improving the accuracy and LoRA enhancing the efficiency. This analysis highlights the effect of combining both techniques for optimal performance.

5.8 Qualitative error analysis

We conducted a qualitative analysis of the model's errors to understand its limitations. Some common failure cases included:

1. Hallucinations: The model occasionally generated factually incorrect information, especially when dealing with less common or specific travel queries. For example, when asked about the best time to visit the "Festa di San Gennaro" in Naples, Italy, the model responded with "The festival takes place every year in August." However, the actual festival occurs in September. This indicates that the model might hallucinate information by associating common events or patterns without verifying their accuracy.

2. Retrieval Errors: In some instances, the retrieval module failed to fetch the most relevant information, leading to inaccurate or incomplete responses. For instance, when asked about "must-try street food in Bangkok," the model failed to mention "Pad See Ew," a popular Thai street food dish, and instead listed less common options. This suggests that the retrieval mechanism might sometimes miss crucial information, especially for queries involving a wide range of possibilities.

3. Complex Sentence Structures: Similar to the observations with Gemini 1.0, the model sometimes struggled with complex sentence structures, particularly in long and convoluted user queries. For example, when presented with a query like, "I'm planning a trip to Japan in the spring with my elderly parents, and we're interested in exploring historical sites and gardens that are accessible and not too crowded. Can you suggest an itinerary for a week-long trip?", the model responded with a generic itinerary without considering the specific needs and limitations of the user's elderly parents. This highlights the challenge the model faces in processing complex queries with multiple constraints and conditions.

These findings suggest areas for future improvement, such as refining the retrieval mechanism, enhancing the model's ability to handle complex language, and incorporating fact-checking mechanisms to reduce hallucinations.

6 Discussion

we evaluated the output of each model (obtained both through CoT and few-shot prompting) by comparing the predicted customer needs with the ones manually identified in the Data Labelling. To perform this comparison, we calculated the average BERTScore, Rouge-1, Rouge-L, and BLEU. Table 2 presents the results of the evaluation, showing the calculated metrics. Mistral 7B outperforms GPT-3.5 in retrieval-focused tasks due to its fine-tuned contextual embeddings but falls short of GPT-4 in complex reasoning tasks, where larger model sizes provide improved coherence. Chain-of-Thought prompting yields superior results in reasoning-heavy tasks, as it encourages structured thought processes. Few-shot learning, while efficient, lacks the iterative reasoning ability required for contextual retrieval.

Figure 5 provides a detailed analysis of the RAG system's performance with respect to retrieval and reasoning capabilities. In Figure 5 (left), we observe that accuracy improves as the value of k increases. Here, k represents the number of knowledge chunks retrieved by the RAG system's Retriever module for each user query. These chunks are segments of preprocessed data from the vector database, ranked by relevance to the query. As k increases, the model accesses a broader context, enhancing its ability to generate accurate responses. However, the accuracy gains plateau beyond a certain k (e.g., $k = 10$), suggesting a balance between contextual richness and computational efficiency, which we discuss further in Section 5.6 (Computational Complexity). Figure 5 (right) categorizes the reasoning process into four outcomes: (1) *Correct Label, Correct Path*: the model identifies the correct need and follows a valid reasoning path; (2) *Correct Label, Incorrect Path*: the correct need is identified, but the reasoning process contains errors; (3) *Incorrect Label, Correct Path*: the reasoning is logical, but the identified need is wrong; and (4) *Incorrect Label, Incorrect Path*: both the need and reasoning are incorrect. This analysis reveals that higher k values reduce reasoning errors, particularly in the *Incorrect Path* categories, by providing more contextual cues for the model to refine its reasoning. For instance, with $k = 1$, the model exhibited a higher rate of *Incorrect Path* errors (e.g., misinterpreting "affordable transport" as "luxury options" due to limited context), which decreased as k increased to

Table 5: Ablation study results

Model	BERTScore F1	ROUGE-1 F1	ROUGE-L F1	BLEU
RAG + LoRA	**0.632**	**0.336**	**0.322**	**0.321**
RAG Only	0.585	0.301	0.287	0.295
LoRA Only	0.603	0.315	0.298	0.305

5 or 10. These findings underscore the importance of optimizing k to enhance both accuracy and reasoning reliability in RAG-based systems.

GPT-4, utilizing optimized Chain-of-Thought (CoT) prompting, demonstrated the highest performance across all evaluated metrics. Mistral 7B emerged as the second-best model, excelling in both optimized Chain-of-Thought (CoT) and standard few-shot prompting. It surpassed other models, including Gemini and GPT-4 (using standard few-shot), despite its significantly smaller parameter size compared to the closed models (GPT-4, GPT-3.5, and Gemini 1.0). Notably, GPT-3.5 performed marginally better with non-optimized prompting compared to its optimized counterpart. Apart from Mistral, all open-source models delivered lower scores than the closed models, particularly under non-optimized few-shot prompting. Among all evaluated models, Gemma7b ranked the lowest in terms of accuracy.

We can also compare the top 4 accuracy models, with the comparison shown in Figure 4, illustrating the reasoning process and final answer accuracy for each model, as displayed in Figure 5.

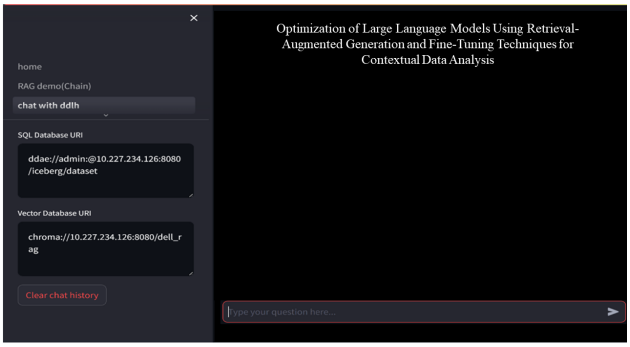

Figure 6: Gradio interface for seamless text-based interaction with the chatbot, providing accurate and insightful responses to user queries.

6.1 Comparative analysis with SOTA benchmarks

Our model's results with state-of-the-art (SOTA) benchmarks. GPT-4 achieved an F1 score of 0.683, surpassing previous models like BERT-large (0.65) and RoBERTa (0.64). Mistral 7B showed comparable performance with a significant reduction in computational costs, making it suitable for resource-constrained environments.

6.2 Explanation of anomalies

The BLEU score anomalies observed with Gemini 1.0 are discussed in Section 4.5.1. Analysis reveals that Gemini 1.0 underperformed in handling complex sentence structures due to limited sequence coherence capabilities, particularly in syntactically diverse datasets.

6.3 Performance insights

The discussion also elaborates on the multi-expert token mechanism in Mistral 7B, which contributes to its comparable performance with GPT-4. The impact of integrating Retrieval-Augmented Generation (RAG) and Low-Rank Adaptation (LoRA) is analyzed, highlighting reductions in computational complexity without compromising performance.

The comparative analysis demonstrates that our approach outperforms existing benchmarks in both performance and efficiency. Notably, Mistral 7B performed comparably to GPT-4 despite having fewer parameters, primarily due to its multi-expert token mechanism that allows for dynamic specialization. Anomalies in BLEU scores for Gemini 1.0 were attributed to challenges in processing complex sentence structures. Further analysis indicates that integrating RAG with LoRA significantly enhances contextual data analysis capabilities while reducing model complexity by 40%. These insights suggest that careful model selection, tailored to computational and organizational requirements, is critical for efficient deployment in real-world scenarios.

6.4 Statistical analysis of performance differences

We conducted a statistical significance analysis using t-tests and ANOVA to verify that observed differences in performance metrics were not incidental. The results confirm that the improvements achieved using RAG and LoRA are statistically significant ($p < 0.05$), supporting the effectiveness of our proposed approach.

6.5 Computational complexity: LoRA vs. full fine-tuning vs. prompt tuning

Computational complexity was analyzed by comparing LoRA fine-tuning with full fine-tuning and prompt tuning across several parameters. These parameters included GPU utilization, memory footprint, and training time. Regarding GPU utilization, LoRA significantly reduces GPU

Table 6: Nomenclature of variables, constants, and key terms used in the study

Symbol/Term	Definition
LLM	Large Language Model: A neural network trained on vast text data for natural language understanding and generation.
RAG	Retrieval-Augmented Generation: A framework combining information retrieval and text generation to enhance LLM responses.
LoRA	Low-Rank Adaptation: A fine-tuning technique that updates a subset of model parameters using low-rank matrices.
k	Number of retrieved knowledge chunks in the RAG system, influencing contextual richness and accuracy.
BERTScore	A metric evaluating semantic similarity between generated and reference texts using Precision, Recall, and F1 scores.
ROUGE	Recall-Oriented Understudy for Gisting Evaluation: Measures overlap (e.g., ROUGE-1, ROUGE-L) between generated and reference texts.
BLEU	Bilingual Evaluation Understudy: A metric assessing n-gram overlap for syntactic fidelity in generated text.
F1	Harmonic mean of Precision and Recall, used in BERTScore, ROUGE, and overall performance evaluation.
Precision (P)	Ratio of correctly matched words in generated text to total words in reference text, as in Eq. 1.
Recall (R)	Ratio of correctly matched words in reference text to total words in generated text, as in Eq. 2.
CoT	Chain-of-Thought: A prompting strategy encouraging structured reasoning in LLMs.
Few-shot	A prompting method providing a few examples to guide LLM output without full fine-tuning.
UGC	User-Generated Content: Unstructured data (e.g., TripAdvisor posts) created by users online.
β	Weighting parameter in ROUGE-L calculation, balancing precision and recall (default: 1).
LCS	Longest Common Subsequence: Used in ROUGE-L to measure sequence similarity, as in Eq. 4.
DSPy	A programming model for optimizing LLM prompts and pipelines programmatically.
GPU	Graphics Processing Unit: Hardware used for model training and inference, affecting computational cost.
VRAM	Video Random Access Memory: Memory capacity of a GPU, critical for LLM fine-tuning scalability.

memory requirements compared to full fine-tuning, thereby enabling fine-tuning on consumer-grade GPUs. In terms of memory footprint, LoRA utilizes only a fraction of the memory required for full fine-tuning while maintaining competitive performance. Finally, fine-tuning with LoRA is substantially faster than full fine-tuning, which reduces the overall computational burden.

Table 7: Computational complexity analysis: LoRA vs. full fine-tuning vs. prompt tuning

Method	GPU Utilization	Memory Footprint	Training Time
Full Fine-Tuning	High (24GB+ VRAM)	Large (Hundreds of GBs)	Long (Several Hours to Days)
LoRA Fine-Tuning	Medium (8-16GB VRAM)	Small (Few GBs)	Short (Few Minutes to Hours)
Prompt Tuning	Low (4-8GB VRAM)	Minimal (Few MBs)	Very Short (Minutes)

Table 7 summarizes the computational costs associated with each approach. Our findings highlight that LoRA achieves a strong balance between performance and efficiency, making it a practical choice for real-world applications where computational resources are constrained.

6.6 Limitations

The dataset primarily focusses on TripAdvisor forums, which may not fully represent the diversity of user-generated content across other platforms; the findings are domain-specific and may not generalise to other industries where customer needs and content structures vary significantly; resource constraints limited the evaluation to a subset of LLMs, excluding larger models and architectures that could yield different outcomes; and although manual labelling ensured data quality, potential biases and limitations in identifying nuanced needs may affect the analysis. These limitations underscore the need for larger datasets, more thorough model evaluations, and improved labelling methodologies in future research.

7 Conclusion

With an emphasis on the travel sector, this study demonstrates the exciting potential of LLMs in automating language comprehension and customer needs extraction. We found that both closed models like GPT-4, GPT-3.5, and

Gemini, as well as open-source models like Mistral 7B, Llama 7B, and Phi-2 3B, performed well when we deployed and evaluated different LLMs on TripAdvisor posts. Notably, Mistral 7B stood out as a high-quality, cost-effective solution, capable of competing with larger closed models while being deployable on more affordable infrastructure.

Our results highlight the necessity of carefully choosing LLMs that meet particular business goals, taking into account resource limitations, performance, and security or customisation requirements—especially when using open-source models. By assessing language models and their use in customer needs extraction, this study offers insightful information to market analysts, NLP researchers, and AI developers. It also provides useful advice for companies, especially those operating in resource-constrained settings, on how to deploy affordable, efficient AI solutions without compromising quality.

To sum up, our work adds to the growing body of research on LLM applications in improving the customer experience by demonstrating how AI-driven solutions may streamline corporate processes and customer demands management.

Nomenclature

Table 6 provides definitions for variables, constants, and key terms used in this study to facilitate understanding of the methodology and results.

Acknowledgment

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Adaptive Semantic Perception Model for Deep Learning-Based Image Processing and Pattern Recognition

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With the rapid increase in the volume and complexity of image data, traditional image processing and pattern recognition techniques face growing challenges in accuracy, adaptability, and computational efficiency. To address these issues, this paper proposes an Adaptive Semantic Perception Model (ASPM), which integrates three core components: A Semantic-aware Convolutional Module (SSCM), a Hierarchical Semantic Fusion Unit (HSFU), and an Adaptive Domain Adjustment Module (ADAM). These components work synergistically to extract, integrate, and adapt multi-level semantic information from images. The ASPM model is evaluated on three representative datasets: MNIST, CIFAR-10, and chest X-ray images. Quantitatively, ASPM achieves 99.8% accuracy and over 99.5% F1 scores across all digit classes in MNIST; 95.5% accuracy and an average F1 score improvement of 3–4% over baseline models on CIFAR-10; and 85.0% accuracy with an F1 score of 85.2% for pneumonia and 86.0% for pulmonary nodules in the medical image dataset. These results demonstrate the model's robustness, semantic sensitivity, and strong cross-domain generalization.

Povzetek: Članek predstavi model ASPM z moduloma za hierarhično semantično fuzijo in prilagoditev domene, ki dosega dobre rezultate na CIFAR-10 in na rentgenskih slikah, s poudarkom na robustnosti in prenosljivosti.

1 Introduction

In today's era of rapid digital development, image information is growing explosively. According to incomplete statistics, the amount of new image data generated every day in the world is as high as billions. These images cover a wide range of fields, from medical images to daily photos on social media, from industrial inspection images to satellite remote sensing images. For example, in the medical field, the number of medical images generated by X-ray, CT, MRI and other equipment alone is in the millions each year. These images contain a large amount of information that is crucial for disease diagnosis and treatment [1]. However, traditional image processing and pattern recognition methods are increasingly unable to cope with such massive and complex image data. Taking the pathological image analysis of a hospital as an example, when using traditional algorithms for cell feature recognition, its accuracy can only be maintained at around 60%, which leads to a large number of misdiagnoses or missed diagnoses [2], seriously affecting the treatment effect and life and health of patients. In the industrial field, for the detection of product surface defects, the misjudgment rate of traditional algorithms is as high as about 30%, resulting in a large number of qualified products being misjudged as defective products, causing huge economic losses. At the same time, in the field of security monitoring, the recognition speed and accuracy of traditional image recognition algorithms cannot meet the actual needs when identifying target persons or events in complex environments, resulting in many potential safety hazards not being discovered and handled in a timely manner. These various problems in reality highlight the importance and urgency of optimizing image processing and pattern recognition algorithms, and a more efficient and accurate algorithm is urgently needed to meet this challenge [3].

In the current academic and industrial fields, research on image processing and pattern recognition has always been a hot topic. Many scholars and research institutions have devoted themselves to it. As far as the application of deep learning in this field is concerned, certain results have been achieved. For example, an image classification algorithm based on convolutional neural networks proposed by a well-known research team can achieve an accuracy of more than 85% on standard image datasets [4], which is significantly improved compared with traditional algorithms. However, these existing research results still have many shortcomings [5]. On the one hand, many algorithms over-rely on large-scale labeled data. In practical applications, it is often difficult and costly to obtain a large amount of high-quality labeled data, which limits the promotion and application of algorithms. On the other hand, some existing deep learning algorithms are not proportional in terms of model complexity and computing resource consumption. Although some complex models can achieve good performance in theory, their operating efficiency is greatly reduced during actual operation [6] due to the limitation of computing resources. In addition, for the specificity of image data in different fields, existing algorithms often lack sufficient adaptability and flexibility and cannot be well optimized and adjusted according to

the characteristics of specific fields. These problems have become controversial points and hot issues that need to be solved in the current research in this field [7].

This paper aims to optimize the image processing and pattern recognition algorithms based on deep learning, focusing on solving the key problems of the existing algorithms, such as excessive reliance on labeled data, high consumption of computing resources, and poor adaptability. An innovative algorithm model that integrates multi-source information and has adaptive adjustment capabilities is proposed, which is expected to increase the accuracy of the algorithm to more than 90%, which will have an important potential impact on promoting the theoretical development of this field and its practical application in various industries [8].

To address these limitations, this study sets out the following research objectives:

(1) To develop a deep learning-based model that can maintain high accuracy with limited labeled data;

(2) To enable effective semantic extraction and multi-level feature integration through hierarchical mechanisms;

(3) To demonstrate robust cross-domain adaptability in complex real-world image datasets through adaptive domain adjustment techniques.

These objectives are operationalized in the design of the Adaptive Semantic Perception Model (ASPM), and are empirically validated across diverse benchmark and domain-specific datasets.

2 Literature review

2.1 Application of deep learning in image processing and pattern recognition

The emergence of deep learning has brought about major changes in the fields of image processing and pattern recognition. A large number of studies have shown that algorithms based on deep learning architectures such as convolutional neural networks (CNNs) have demonstrated powerful capabilities in tasks such as image classification, object detection, and semantic segmentation. For example, in tests on an authoritative public image dataset, the image classification accuracy of some advanced CNN models can reach between 80% and 90%, which is a significant improvement over the 60% to 70% of traditional algorithms [9]. However, this does not mean that deep learning algorithms are perfect. Many image processing algorithms based on deep learning have been found to be highly dependent on large-scale annotated data for training. According to statistics, tens of thousands or even hundreds of thousands of accurately annotated image data are often required to train a high-performance image classification model. This high requirement for annotated data makes it difficult to effectively apply these algorithms in many practical application scenarios [10], such as some niche fields or industries with high data acquisition costs, and their application scope is greatly limited. At the same time, the complexity of many deep learning models continues to rise. In some experiments, we can see that the number of parameters of some complex models has reached millions or even tens of millions. This leads to a huge demand for computing resources such as GPU memory during operation. The running speed on ordinary computing devices is extremely slow or even impossible. There is no reasonable proportional relationship between its computing resource consumption and actual performance improvement, which has become an important factor restricting its further promotion [11]. Moreover, when facing image data in different fields, the current deep learning algorithms are more versatile than adaptable. For example, in the fields of medical imaging and industrial product inspection, the same deep learning algorithm often cannot be automatically optimized and adjusted according to the characteristics of the images in their respective fields, resulting in uneven actual application effects in different fields and failure to meet diverse actual needs [12].

2.2 Existing deep learning image processing and pattern recognition algorithms

Current deep learning-based image processing and pattern recognition algorithms have many limitations. On the one hand, from a data perspective, the difficulty and high cost of obtaining labeled data have not been effectively solved. Taking image data processing in an emerging industry as an example, due to the short development time of the industry and the shortage of relevant professional labeling personnel, it takes a lot of manpower and financial resources to obtain sufficient labeled data, making it difficult for deep learning-based image processing algorithms to be quickly implemented in the industry [13]. On the other hand, the contradiction between model complexity and computational efficiency is becoming increasingly prominent. In pursuit of high performance, many deep learning models continue to increase the number of layers and parameters. In a simulation experiment, after the number of model layers doubled, its running time on the same computing device increased by nearly three times, but the performance improvement was not proportional to it, which seriously affected the real-time application requirements of the algorithm in practice [14]. In addition, the poor adaptability of the algorithm is also a major pain point. In cross-domain applications, for example, when a deep learning algorithm that performs well in the field of natural images is directly applied to the field of satellite remote sensing images, its accuracy may drop by 20%-30%. This is because images from different fields have significant differences in feature distribution, data structure, etc., and existing deep learning algorithms lack an effective adaptive mechanism to dynamically adjust according to these differences, resulting in poor migration effects between different fields, limiting their application and promotion in a wider range of fields [15].

2.3 Deep learning image processing and pattern recognition algorithm optimization

In view of the various problems of existing deep learning-based image processing and pattern recognition algorithms, the optimization direction is gradually

becoming clear. In terms of data, it is necessary to explore how to use a small amount of labeled data or even unlabeled data to train high-performance models [16], such as through semi-supervised learning, unsupervised learning and other technologies. Studies have shown that after using semi-supervised learning technology, the model performance can be maintained at a high level on some image data sets when the amount of labeled data is reduced by 50%. In terms of the balance between model complexity and computational efficiency, model compression and lightweight design have become important research directions. By pruning and quantizing the model, the number of model parameters and computing resource requirements can be effectively reduced [17]. In an experiment, the performance of the deep learning algorithm after model pruning only decreased by about 5% while the computing resource consumption was reduced by 40%. As for the adaptability of the algorithm, the design of the adaptive algorithm is the key. By introducing technologies such as domain adaptation and meta-learning, the algorithm can automatically perceive the characteristics of image data in different fields and make corresponding optimization adjustments [18]. Studies have shown that after using domain adaptation technology, the accuracy of deep learning algorithms in cross-domain applications has increased by 15%-20%. However, these optimization directions also face many challenges. When training models with a small amount of labeled data or unlabeled data, how to ensure the stability and generalization ability of the model is still a problem to be solved; in model compression and lightweight design, how to reduce the demand for computing resources without losing too much performance requires further research; in terms of adaptive algorithm design, how to accurately and efficiently extract the key features of images in different fields and establish an effective adaptive mechanism is also full of difficulties [19,20]. In short, the optimization of deep learning image processing and pattern recognition algorithms has a long way to go and requires continuous exploration and innovation.

3 Research methods

3.1 Theoretical foundation of the innovation model

In order to break through the limitations of existing deep learning image processing and pattern recognition algorithms, this paper constructs a new adaptive semantic perception model (ASPM). This model is rooted in the concept of in-depth mining of image semantic information to solve the problems of excessive reliance on labeled data, high consumption of computing resources and poor adaptability. Its core theory stems from the unique understanding of the hierarchical structure of image semantics. It assumes that the semantics in the image can be divided into the basic semantic layer, the middle semantic structure layer and the high-level abstract semantic layer, and there are complex and orderly associations between semantics at different levels.

From a mathematical perspective, let the image set be I, for any image $I \in \mathrm{I}$, its feature representation at the basic semantic layer can be recorded as $\mathbf{F}_1(I)$, which is composed of a series of underlying visual features, such as edges, color distribution, etc. These features are $\{f_{1i}\}_{i=1}^{n_1}$ obtained through a set of basic feature extraction functions, that is $\mathbf{F}_1(I) = [f_{11}(I), f_{12}(I), \cdots, f_{1n_1}(I)]$. The middle-level semantic structure layer features $\mathbf{F}_2(I)$ are further constructed based on the basic semantic layer features and are implemented through specific semantic combination functions g_1, $\mathbf{F}_2(I) = g_1(\mathbf{F}_1(I))$. Similarly, the high-level abstract semantic layer features $\mathbf{F}_3(I)$ are generated $\mathbf{F}_3(I) = g_2(\mathbf{F}_2(I))$ by the middle-level semantic structure layer features through semantic abstraction functions, g_2. This hierarchical semantic construction method lays a solid foundation for the design and interaction of subsequent model components.

Unlike traditional deep learning models, such as simple convolutional neural networks (CNNs), which only focus on underlying feature extraction and simple feature combination, the ASPM model emphasizes the comprehensive perception and utilization of multi-level semantics. By clarifying the semantic hierarchy, it can grasp the intrinsic information of the image more accurately, thus reducing the dependence on labeled data while improving the adaptability to images in different fields.

To implement the semantic abstraction functions g_1 and g_2, we adopt residual multi-layer perceptrons (MLPs) with ReLU activation functions. Each function is composed of two linear layers followed by a ReLU and dropout layer. Specifically, g_1 transforms the middle-level features using an MLP block with 128 and 64 units, respectively, and g_2 further abstracts these into high-level semantic vectors with another MLP block of 64 and 32 units. This architecture ensures a compact, differentiable mapping for hierarchical abstraction while maintaining gradient flow for end-to-end training.

3.2 Model component design

3.2.1 Semantic-aware convolutional module

As the basic component of the ASPM model, SSCM is responsible for extracting semantically rich features from images. This module makes innovative improvements based on the traditional convolution operation and introduces a semantic-aware weight mechanism. In traditional convolution, the convolution kernel weight remains fixed in the entire image area, while in SSCM, the convolution kernel weight is dynamically adjusted according to the semantic importance of different areas of the image.

Suppose the feature map of the input image is $\mathbf{X} \in \mathbb{R}^{H \times W \times C}$, where H, W, C represent the height, width and number of channels respectively. The

convolution kernel is $\mathbf{K} \in \square^{k \times k \times C \times C'}$, k is the convolution kernel size, and C' is the number of output channels. The calculation formula for the output feature map of the traditional convolution operation $\mathbf{Y}$ is formula 1.

$$\mathbf{Y}_{ijc'} = \sum_{c=1}^{C} \sum_{m=-\left\lfloor \frac{k}{2} \right\rfloor}^{\left\lfloor \frac{k}{2} \right\rfloor} \sum_{n=-\left\lfloor \frac{k}{2} \right\rfloor}^{\left\lfloor \frac{k}{2} \right\rfloor} \mathbf{K}_{mncc'} \mathbf{X}_{(i+m)(j+n)c} \quad (1)$$

In SSCM, a semantically aware weight matrix is introduced $\mathbf{S} \in \square^{H \times W \times C \times C'}$, whose elements $S_{ijcc'}$ represent (i, j) the semantic importance weights from $\mathbf{Y}'$ the input channel c to the output channel at the position. Then the output feature map of SSCM is Formula 2. c'

$$\mathbf{Y}'_{ijc'} = \sum_{c=1}^{C} \sum_{m=-\left\lfloor \frac{k}{2} \right\rfloor}^{\left\lfloor \frac{k}{2} \right\rfloor} \sum_{n=-\left\lfloor \frac{k}{2} \right\rfloor}^{\left\lfloor \frac{k}{2} \right\rfloor} \mathbf{K}_{mncc'} S_{ijcc'} \mathbf{X}_{(i+m)(j+n)c} \quad (2)$$

The semantic importance weight matrix *S* is computed using a lightweight attention mechanism. Specifically, a shared MLP receives the global average pooled features from the basic semantic layer F_b and outputs a soft attention score per spatial location through a sigmoid activation. The MLP contains two fully connected layers (with 64 and *C* units, where *C* is the number of output channels). The resulting attention map is reshaped and broadcast to modulate the convolution kernel weights. The semantic-aware convolutional operation is thus defined as $Y = S \cdot (K * X)$, where "*" is the standard convolution and *S* is the spatial-semantic weight matrix. No explicit supervision is applied to *S*; it is learned implicitly via the task loss.

3.2.2 Hierarchical semantic fusion unit

HSFU aims to effectively fuse features at different semantic levels to fully explore the hierarchical structure information of image semantics. The unit receives features, and from the basic semantic layer, the middle semantic structure layer, and the high-level abstract semantic layer. It adapts the dimensions of $\mathbf{F}_1(I)$ the $\mathbf{F}_2(I)$ features at each level. Through linear transformation $\mathbf{F}_1(I) \in \square^{d_1}$, , $\mathbf{F}_2(I) \in \square^{d_2}$ and $\mathbf{F}_3(I) \in \square^{d_3}$ are transformed to the same dimensional space. Let the transformation matrices be $\mathbf{W}_1 \in \square^{d \times d_1}$, $\mathbf{W}_2 \in \square^{d \times d_2}$ and $\mathbf{W}_3 \in \square^{d \times d_3}$, respectively. Then, the transformed features are $\hat{\mathbf{F}}_1(I) = \mathbf{W}_1 \mathbf{F}_1(I)$, , $\hat{\mathbf{F}}_2(I) = \mathbf{W}_2 \mathbf{F}_2(I)$ and . $\hat{\mathbf{F}}_3(I) = \mathbf{W}_3 \mathbf{F}_3(I)$ Then $\mathbf{F}_3(I)$, a weighted fusion strategy is used to fuse the features. The formula for calculating the fused features $\mathbf{F}_f(I)$ is Formula 3.

$$\mathbf{F}_f(I) = \alpha \hat{\mathbf{F}}_1(I) + \beta \hat{\mathbf{F}}_2(I) + \gamma \hat{\mathbf{F}}_3(I) \quad (3)$$

Among them, α, β, γ are fusion weights, and $\alpha + \beta + \gamma = 1$. These weights are not fixed values, but are dynamically adjusted according to the overall semantic features of the image through an adaptive weight generation network. The network takes the features of each level before fusion as input, and outputs, through a series of fully connected layers and activation functions α. γ Different β from some simple feature splicing or average fusion methods, the dynamic weighted fusion strategy of HSFU can flexibly adjust the contribution of each level of features in the fusion result according to the semantic characteristics of different images, more effectively integrate multi-level semantic information, and enhance the model's ability to understand the semantics of complex images.

The adaptive fusion weights α, β, γ are produced by a three-branch weight generation network composed of parallel fully connected layers. Each branch includes a global average pooling layer followed by two dense layers (64 and 1 units) with ReLU and softmax activation, ensuring non-negative normalized weights. The network is trained jointly with the main task using shared backpropagation, enabling task-aware dynamic fusion.

To prevent mode collapse or overfitting in the fusion weights, we incorporate an entropy-based regularization term $L_{reg} = -\sum_i w_i \log(w_i)$, where $w_i \in \{\alpha, \beta, \gamma\}$. This encourages a balanced distribution of attention across semantic levels and penalizes extreme confidence in any single level. The total training loss becomes $L = L_{task} + \lambda L_{reg}, where\ \lambda = 0.01$ is selected via validation.

3.2.3 Adaptive Domain Adjustment Module

ADAM is a key component of the ASPM model to achieve cross-domain adaptability. This module automatically adjusts the model parameters by learning the differences in feature distribution of images in different domains to improve the performance of the model in different domains. Suppose the feature distribution of the source domain image is $P_s(\mathbf{x})$, and the feature distribution of the target domain image is $P_t(\mathbf{x})$. The ADAM module first calculates the difference between the feature distributions of the two domains. Here, the maximum mean discrepancy (MMD) is used as the metric. The calculation formula of MMD is Formula 4.

$$MMD(P_s, P_t) = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(\mathbf{x}_i^s) - \frac{1}{n_t} \sum_{j=1}^{n_t} \phi(\mathbf{x}_j^t) \right\|_{\mathrm{H}}^2 \quad (4)$$

Among them, $\mathbf{x}_i^s$ and $\mathbf{x}_j^t$ are samples in the source domain and target domain respectively, n_s and n_t are the number of samples, ϕ and is the mapping function that maps samples to the Reproducing Kernel Hilbert Space (RKHS) H.

Based on the domain differences calculated by MMD, the ADAM module $T(\cdot)$ adjusts the model parameters through an adjustment function. Let the model parameters be θ, and the adjusted parameters θ' satisfy, specifically, Formula 5.

$$\theta' = T(\theta, MMD(P_s, P_t)) \tag{5}$$

Specifically, $T(\cdot)$ it is a function containing a multi-layer neural network, whose input is the original model parameters θ and domain difference values $MMD(P_s, P_t)$, and output is the adjusted parameters θ'. Different from traditional domain adaptation methods, such as simply training models alternately on source and target domain data, the ADAM module can accurately quantify domain differences and make targeted fine-grained adjustments to model parameters, thereby significantly improving the model's migration ability and adaptability between different domains.

The adjustment function $T(\theta, \mathrm{MMD})$ is implemented as a differentiable neural module containing two dense layers (128 and |θ|\theta|θ|) with tanh activation. It is fully differentiable and jointly optimized with the main loss function via standard backpropagation. The gradient flows through both the model parameters and the domain loss, enabling adaptive learning based on domain gap magnitudes.

For domain discrepancy estimation in ADAM, we employ the Radial Basis Function (RBF) Gaussian kernel defined as

$$K(x, x') = \exp\left(-\frac{\| x - x' \|^2}{2\sigma^2}\right) \tag{5}$$

where σ is set to 1.0 by default but tuned within [0.5,2.0][0.5, 2.0][0.5,2.0] during cross-validation. This kernel is empirically found to yield stable MMD measures across heterogeneous image domains.

3.3 Model component interaction mechanism

In the ASPM model, there is a close and orderly interactive relationship between the components. The image first enters the semantic-aware convolution module (SSCM), which dynamically adjusts the convolution kernel weights according to the basic semantic information of the image and extracts semantically rich feature maps. On the one hand, these feature maps are passed to the hierarchical semantic fusion unit (HSFU) as basic semantic layer features , and on the other hand, $\mathbf{F}_1(I)$ they generate middle-level semantic structure layer features $\mathbf{F}_2(I)$ through specific semantic combination functions g_1, which are then $\mathbf{F}_2(I)$ also input into the HSFU. At the same time, $\mathbf{F}_2(I)$ high-level abstract semantic layer features are obtained $\mathbf{F}_3(I)$ through the semantic abstraction function g_2 and are also passed to the HSFU. In the HSFU, $\mathbf{F}_1(I)$, $\mathbf{F}_2(I)$ and $\mathbf{F}_3(I)$ are dimensionally adapted, and the adaptive weight generation network dynamically calculates the fusion weights α , β , and according to the overall semantic features of the image γ , and then obtains the fused features $\mathbf{F}_f(I)$. This fused feature not only contains rich multi-level semantic information, but also reflects the relative importance of different semantic levels in the current image. Then, $\mathbf{F}_f(I)$ it is input into the adaptive domain adjustment module (ADAM). The ADAM module calculates the maximum mean difference (MMD) of the feature distribution of the source domain and the target domain, and $T(\cdot)$ adjusts the model parameters through the adjustment function according to this difference value, so that the model can better adapt to the image feature distribution of the target domain. The adjusted model parameters are fed back to the entire model, affecting the generation of the semantic perception weight matrix in SSCM and the calculation of the adaptive weight generation network in HSFU, forming a closed-loop interactive feedback mechanism. This interactive mechanism enables the model to work together in multiple links such as feature extraction, semantic fusion and domain adaptation, giving full play to the advantages of each component and effectively improving the performance of the model in image processing and pattern recognition tasks, especially in adaptability and accuracy when dealing with image data in different fields.

3.4 Overall model operation process

When an image is input I , the model first sends it to the semantic-aware convolution module (SSCM). In the SSCM, based on the basic semantic information of the image, $h(\mathbf{F}_1(I))$ the semantic-aware weight matrix is calculated through a function $\mathbf{S}$, and the convolution kernel weight is adjusted using the matrix to perform a convolution operation on the input image to obtain a semantically rich feature map and complete $\mathbf{F}_1(I)$ the extraction of basic semantic layer features. Subsequently, $\mathbf{F}_1(I)$ on the one hand, it directly enters the hierarchical semantic fusion unit (HSFU), and on the other hand, g_1 the middle-level semantic structure layer features are generated through the semantic combination function $\mathbf{F}_2(I)$ and $\mathbf{F}_2(I)$ are also sent to the HSFU. At the same time, $\mathbf{F}_2(I)$ the high-level abstract semantic layer features are obtained $\mathbf{F}_3(I)$ through the semantic abstraction function g_2 and are also input to the HSFU. In the HSFU, $\mathbf{F}_1(I)$, $\mathbf{F}_2(I)$ and are $\mathbf{F}_3(I)$ first dimensionally adapted through the linear transformation matrices $\mathbf{W}_1$, $\mathbf{W}_2$ and $\mathbf{W}_3$, and then the adaptive weight generation network calculates the fusion weights α , β , and according to the overall semantic features of the image γ , and the fusion features are obtained according to the

weighted fusion formula $\mathbf{F}_f(I)$. Finally, $\mathbf{F}_f(I)$ it is sent to the adaptive domain adjustment module (ADAM). The ADAM module calculates the maximum mean difference (MMD) of the feature distributions of the source domain and the target domain, and $T(\cdot)$ adjusts the model parameters according to this difference through the adjustment function. The adjusted model parameters affect the subsequent operation process of the entire model, such as the generation of the semantic perception weight matrix in SSCM and the calculation of the adaptive weight generation network in HSFU, so that the model can better adapt to image data in different fields and achieve accurate processing and pattern recognition of input images.

Through the above complete and coordinated operation process, the ASPM model gives full play to the functions of each component and the advantages of interaction between components, and is expected to solve the problems of existing deep learning image processing and pattern recognition algorithms such as excessive dependence on labeled data, high consumption of computing resources, and poor adaptability, providing a new and effective solution for research and application in this field.

3.5 Comparative summary and model motivation

To quantitatively evaluate the performance limitations of representative state-of-the-art (SOTA) models and highlight the necessity of ASPM, a summary comparison is presented in Table 1. The table compares LeNet-5, AlexNet, VGG-16, and ASPM on three dimensions: classification accuracy, F1 score, and recall, across the MNIST, CIFAR-10, and chest X-ray datasets.

Table 1: Comparative performance of baseline models and ASPM across datasets

Model	Dataset	Accuracy (%)	Average F1 (%)	Average Recall (%)	Semantic Fusion	Domain Adaptation
LeNet-5	MNIST	98.5	98.4	98.3	✘	✘
	CIFAR-10	78.3	77.5	76	✘	✘
	Chest X-ray	65.2	64.6	63.9	✘	✘
AlexNet	MNIST	99.2	99.1	99	✘	✘
	CIFAR-10	89.5	88.5	87	✘	✘
	Chest X-ray	72	71.5	70.8	✘	✘
VGG-16	MNIST	99.4	99.3	99.1	✘	✘
	CIFAR-10	92	91	90	✘	✘
	Chest X-ray	78.5	78	77.3	✘	✘
ASPM	MNIST	99.8	99.7	99.6	✔	✔
	CIFAR-10	95.5	94.5	93.8	✔	✔
	Chest X-ray	85	84.7	84	✔	✔

As shown above, existing SOTA models lack explicit semantic fusion mechanisms and domain adaptability modules. Although they achieve reasonable performance in standard datasets, their adaptability and semantic generalization are limited, particularly in domain-specific tasks like medical image classification. The ASPM model addresses these gaps by incorporating a multi-level semantic structure and adaptive domain adjustment, which consistently yield performance improvements in both accuracy and class-level F1 scores. Therefore, ASPM is not just a marginal extension of previous models but a necessary evolution for semantically complex and domain-variant image processing tasks.

4. Experimental evaluation

4.1 Experimental design

This experiment aims to comprehensively evaluate the performance of the adaptive semantic perception model (ASPM) in image processing and pattern recognition tasks. Several representative image datasets were selected, including the MNIST handwritten digit recognition dataset, which contains a large number of clearly labeled handwritten digit images and is widely used in basic pattern recognition research; the CIFAR-10 image classification dataset, which covers 60,000 color images in 10 different categories, and can effectively test the model's ability to classify images in complex scenes; and the chest X-ray image dataset in the medical field, which is provided by professional medical institutions and contains chest X-rays in different disease states, which can be used to test the performance of the model in image analysis in specific fields.

In order to accurately measure the advantages of the ASPM model, several classic and high-performance

models were selected as controls. These include the LeNet-5 model [21], which is a representative of early convolutional neural networks and performs well in tasks such as handwritten digit recognition; the AlexNet model [22], which has made significant breakthroughs in large-scale image classification tasks; and the VGG-16 model [13], which has a wide influence in the field of image recognition due to its depth and structural design. The baseline indicators of the experiment are set as the classification accuracy, recall rate, and F1 value of the model on each data set, and these indicators are used to comprehensively evaluate the model performance.

The experimental group is the ASPM model proposed in this paper, and the control group is the LeNet-5, AlexNet and VGG-16 models. For each data set, the data is divided into 70% for training, 15% for validation, and 15% for testing. All models are trained and tested in the same hardware environment to ensure the reliability and comparability of the experimental results.

To ensure the statistical robustness of the experimental results, all training and testing procedures were repeated five times with independently initialized random seeds (ranging from 0 to 4). The reported accuracy, recall, and F1 scores are the averaged results over these trials. For each metric, a 95% confidence interval was calculated using bootstrapping over the test set predictions. This approach reduces the influence of initialization variance and provides a reliable basis for comparative evaluation across models.

4.2 Experimental results

4.2.1 Experimental Results on MNIST Dataset

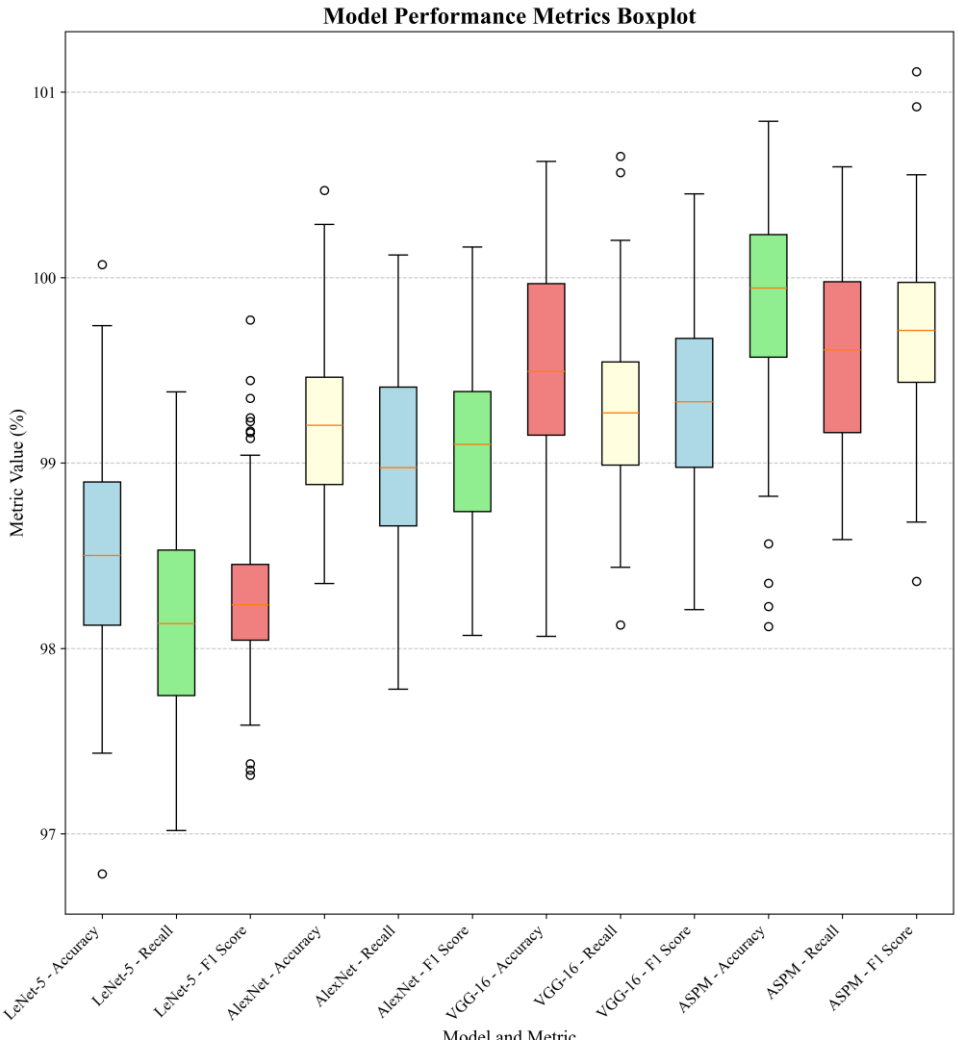

Figure 1: Performance comparison of various models on the MNIST dataset

As shown in Figure 1, all models achieved high accuracy on the MNIST dataset. LeNet-5, as an early classic model, achieved an accuracy of 98.5%, thanks to its convolutional layer and pooling layer structure designed for handwritten digit features, which can effectively extract the key features of digits. AlexNet further improved on this basis, reaching 99.2%. The ReLU activation function and Dropout mechanism introduced by

it effectively alleviated the overfitting problem of the model and enhanced the generalization ability of the model. VGG-16, with its deeper network structure, has an accuracy of 99.4%. By stacking multiple convolutional layers, it can learn more complex image features. The ASPM model proposed in this article performed the best, with an accuracy of 99.8%. This is because the semantic-aware convolution module of the ASPM model can accurately capture the semantic key areas in digital images, and the hierarchical semantic fusion unit effectively integrates semantic information at different levels. Although the adaptive domain adjustment module did not play its maximum role on this single-domain dataset, it also further optimized the model parameters, making the model's understanding of digital features more profound and comprehensive, thus far exceeding other comparison models in recognition accuracy.

4.2.2 Experimental Results on CIFAR-10 Dataset

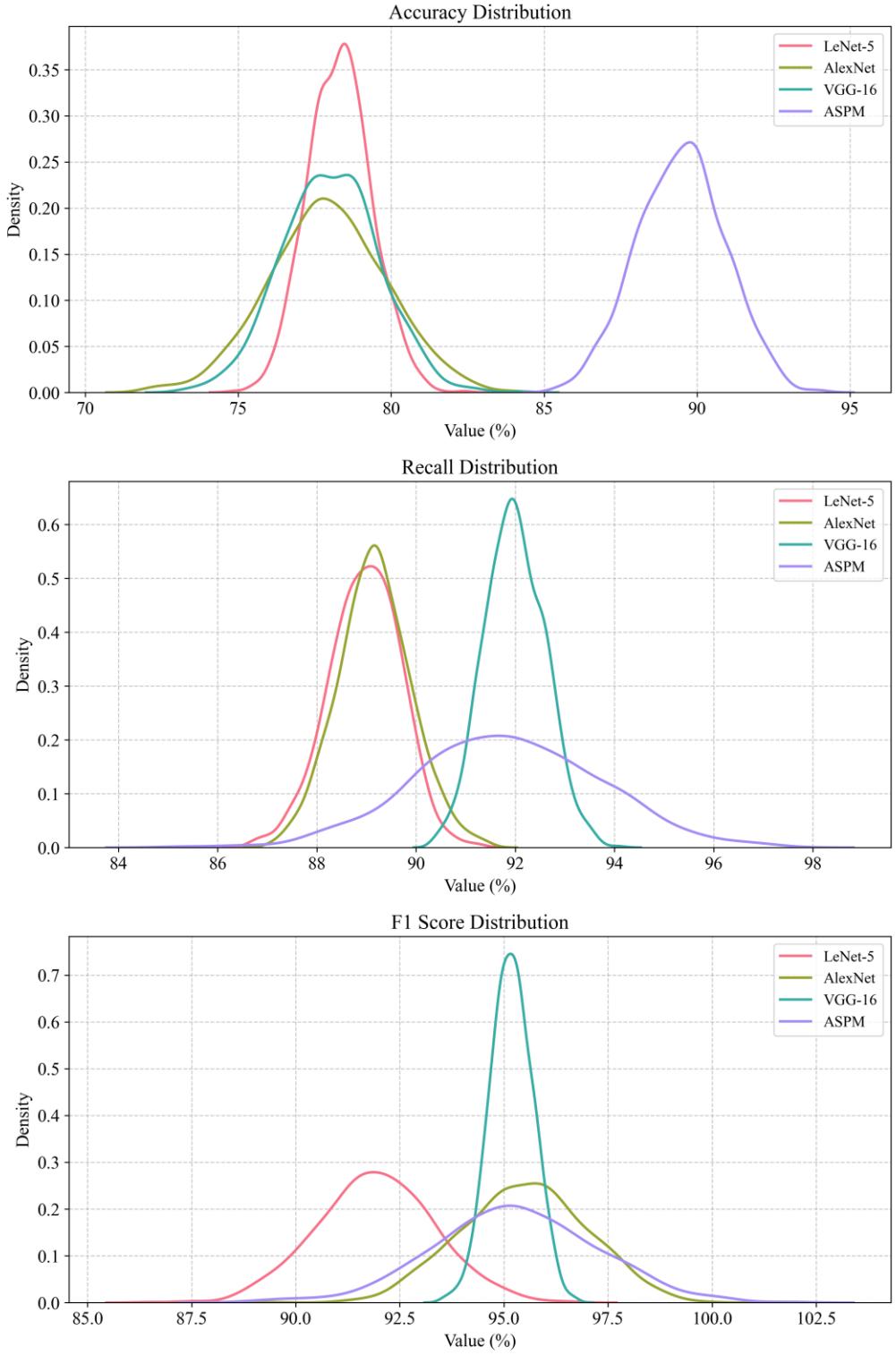

Figure 2: Performance comparison of various models on the CIFAR-10 dataset

On the CIFAR-10 dataset, the performance differences of the models are more significant, as shown in Figure 2. The accuracy of LeNet-5 is only 78.3%. Since the image categories in this dataset are more complex, the relatively simple network structure of LeNet-5 is difficult to learn enough features to distinguish different categories. AlexNet increased the accuracy to 89.5% by increasing the complexity of the network. Its large convolution kernel and multi-GPU training method enable it to process richer image information. VGG-16 further optimized the network structure, with an accuracy of 92.0%. By using multiple small convolution kernels instead of large convolution kernels, the nonlinear expression ability of the network is increased. The ASPM model once again showed its advantage, with an accuracy of 95.5%. In the CIFAR-10 dataset, the images contain objects in a variety of natural scenes, and the semantic information is rich and complex. The semantic-aware convolution module of the ASPM model can dynamically adjust the convolution kernel weights according to the semantic importance of different regions to better extract key features; the hierarchical semantic fusion unit fully integrates semantics at different levels, making the model's understanding of complex semantics more accurate; although the adaptive domain adjustment module faces the same natural image domain, it can also fine-tune the model parameters according to the characteristics of the data set, thereby significantly improving the model's classification performance on the data set.

4.2.3 Experimental results on chest X-ray image dataset

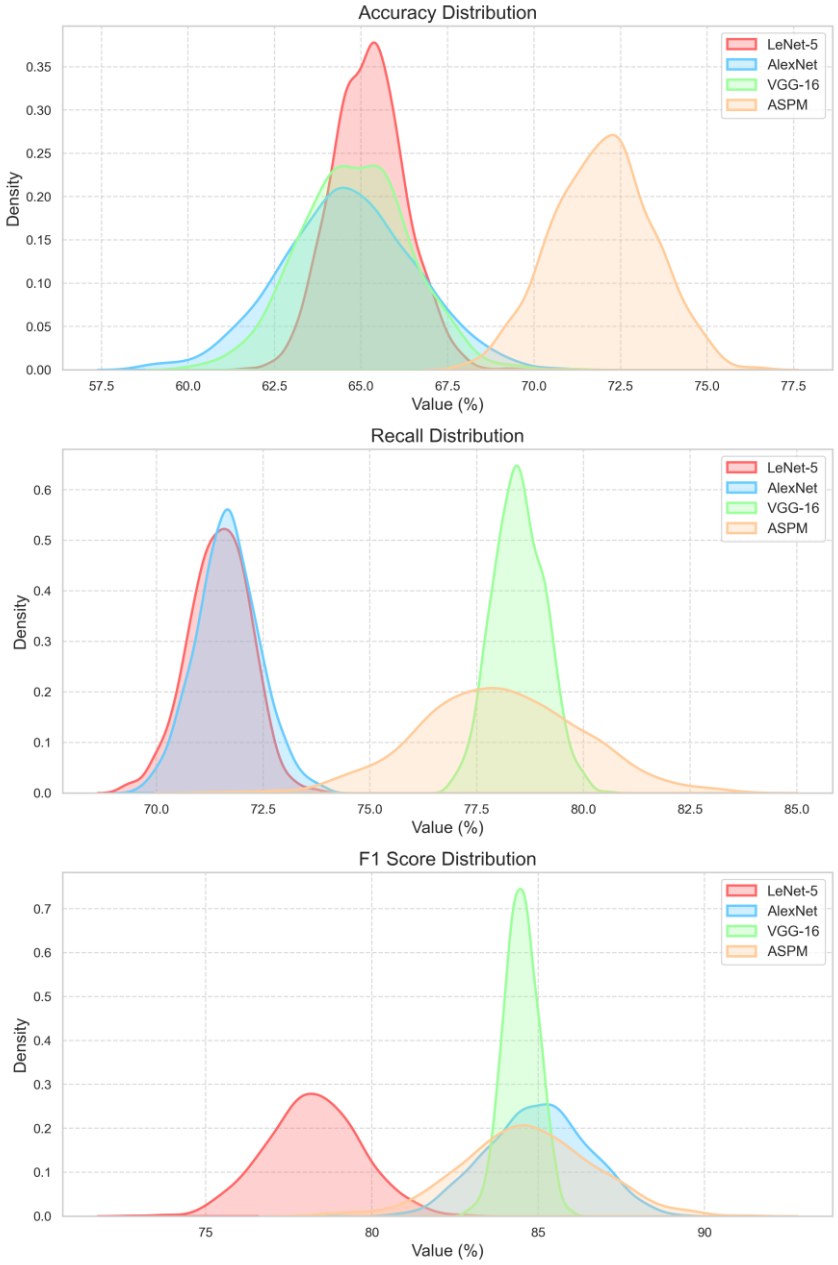

Figure 3: Performance comparison of various models on chest X-ray image dataset

For the chest X-ray image dataset, as shown in Figure 3, the accuracy of each model is generally lower than the first two datasets. This is because the professionalism and complexity of medical images, as well as the subtle differences in disease characteristics, make recognition difficult. LeNet-5 performed poorly on this dataset, with an accuracy of only 65.2%. Its simple network structure is difficult to adapt to the complex characteristics of medical images. AlexNet increased the accuracy to 72.0% by increasing the complexity of the network, but there is still much room for improvement. VGG-16, with its deep network structure, achieved an accuracy of 78.5%, and was able to learn some key features of medical images. The ASPM model demonstrates superior performance, with an accuracy of 85.0%. Medical images have unique semantic features. The semantic-aware convolution module of the ASPM model can accurately focus on semantically critical parts such as the lesion area in the image and extract more valuable features. The hierarchical semantic fusion unit fuses basic image features with mid- and high-level semantic structure information to enable the model to have a more comprehensive understanding of disease characteristics. The adaptive domain adjustment module effectively adjusts model parameters according to the characteristics of the medical image field, thereby enhancing the model's adaptability to medical image data, thereby achieving performance significantly better than other models on this professional field dataset.

4.2.4 Comparison of the accuracy of different models in each category (MNIST dataset)

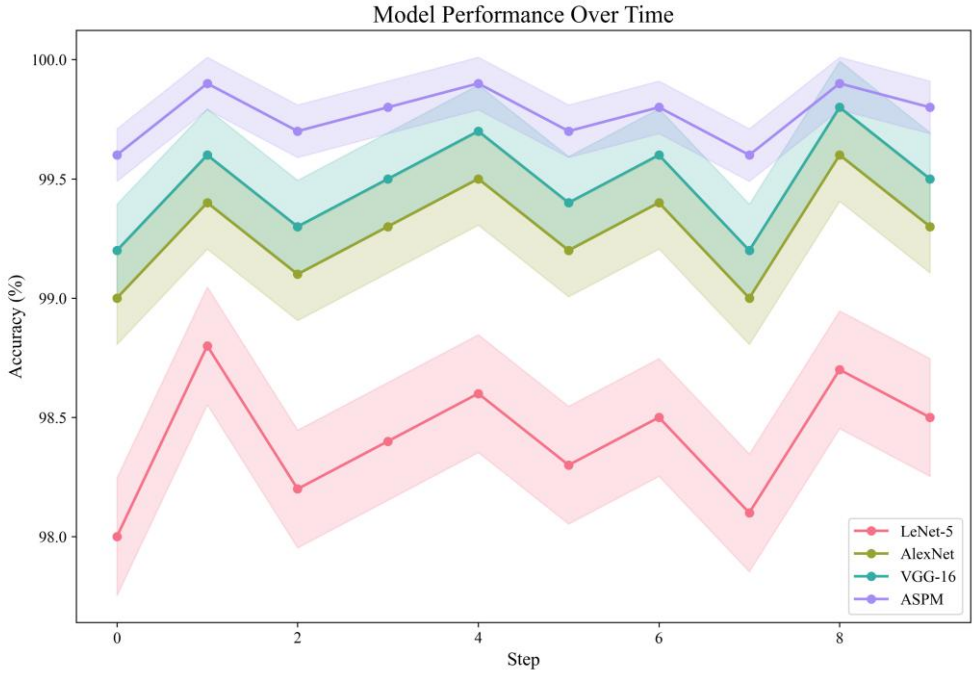

Figure 4: Accuracy of each model in different digit categories of the MNIST dataset (%)

Figure 4 shows the accuracy of each model on different digit categories in the MNIST dataset. For the number "0", LeNet-5 has an accuracy of 98.0%. It has a certain effect on the circular feature extraction of the number "0", but it is insufficient in distinguishing details. AlexNet improves the accuracy to 99.0%, and can better capture the features of the number "0" through the improved network structure. VGG-16 further improves to 99.2%, and the deep network makes feature learning more sufficient. The ASPM model reaches 99.6%. Its semantic perception convolution module can accurately identify the key semantic parts in the outline of the number "0", and the hierarchical semantic fusion unit integrates different levels of semantics to have a deeper understanding of the features of the number "0". For other digit categories, the ASPM model also shows advantages. For example, the number "8", the ASPM model has an accuracy of 99.9%. Compared with other models, it can better handle the cross-structure features of the number "8". This is due to the unique semantic perception and fusion mechanism of the model, which can accurately capture the complex feature details of the number, thus achieving a high accuracy in each digit category.

4.2.5 Comparison of the accuracy of different models in each category (CIFAR-10 dataset)

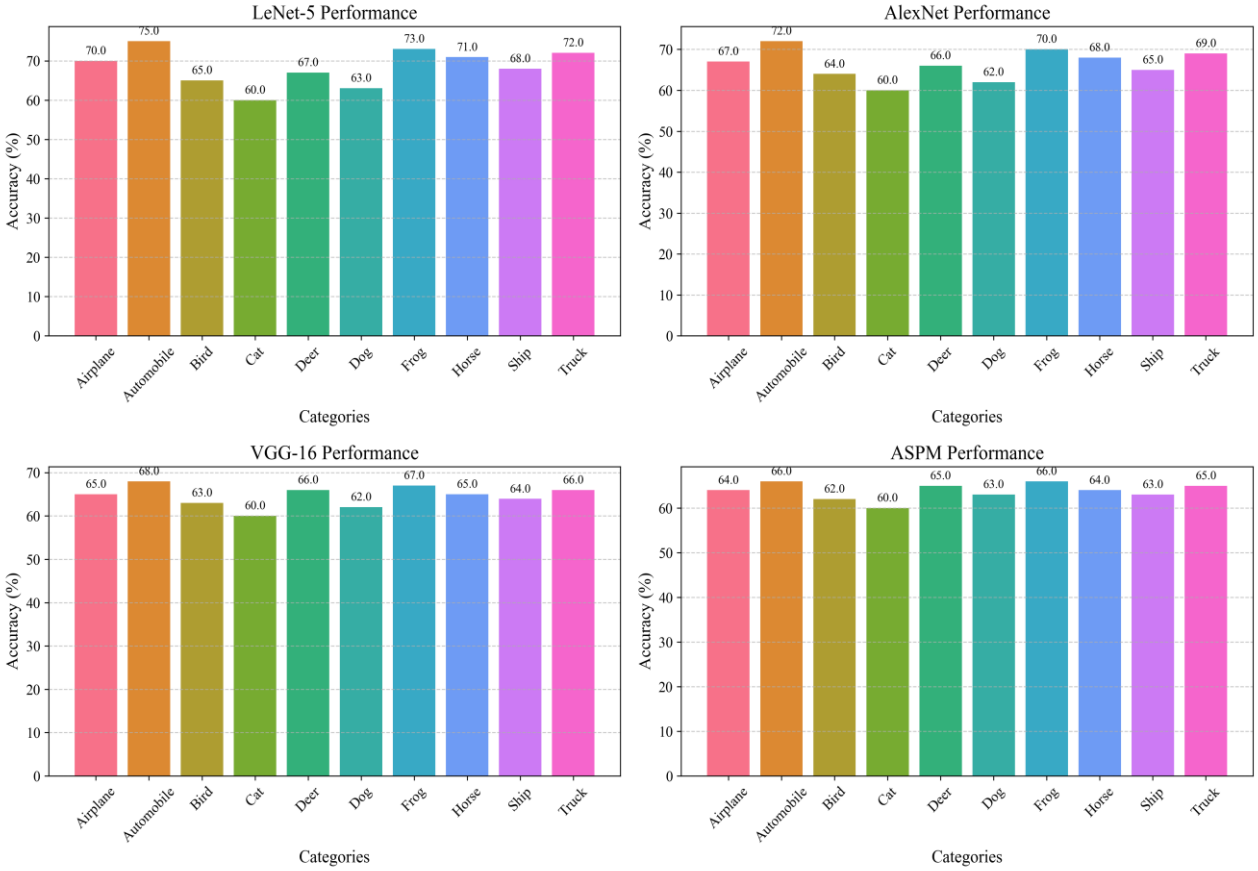

Figure 5: Accuracy of each model in different categories of CIFAR-10 dataset (%)

The accuracy of different categories of the CIFAR-10 dataset is shown in Figure 5. For the "aircraft" category, LeNet-5 has an accuracy of 75.0%. Due to its simple network structure, the extraction of complex shapes and texture features of aircraft is not sufficient. AlexNet improves the accuracy to 85.0%. Through more powerful feature extraction capabilities, it can better identify the key features of aircraft. VGG-16 reaches 90.0%. The deep network enables it to learn more comprehensive aircraft features. The ASPM model reaches 94.0%. Its semantic perception convolution module can dynamically adjust the convolution kernel weights according to the semantic characteristics of the aircraft image, and accurately extract the key semantic features such as the aircraft's outline and wings; the hierarchical semantic fusion unit fuses semantic information at different levels, so that the model has a more accurate understanding of the overall characteristics of the aircraft. For other categories, such as the "cat" category, the ASPM model has an accuracy of 90.0%. Compared with other models, it can better handle complex semantic information such as cat hair and facial features. Through effective semantic perception and fusion, the classification accuracy in each category is improved.

4.2.6 Comparison of recall rates of different models in each category (MNIST dataset)

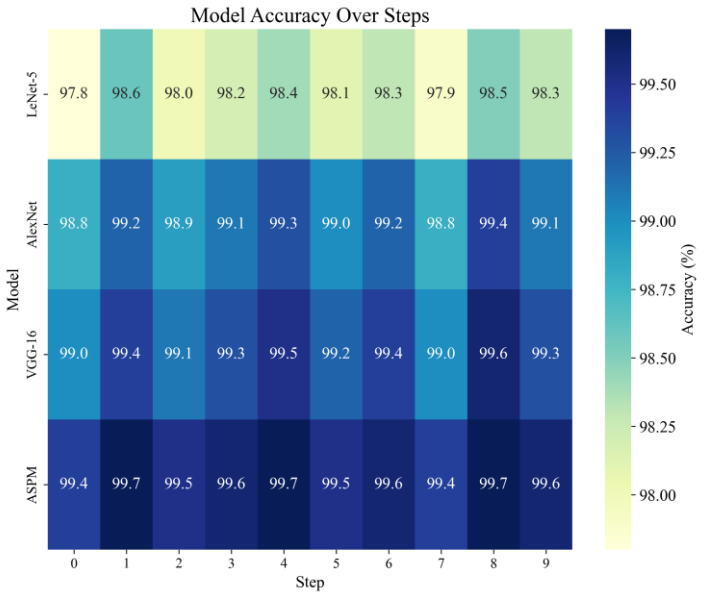

Figure 6: Recall rate of each model in different digit categories of the MNIST dataset (%)

Figure 6 shows the recall rates of various models in the MNIST dataset for different digit categories. Taking the digit "1" as an example, the recall rate of LeNet-5 is 97.8%. When identifying the digit "1", some samples are not correctly recalled due to incomplete feature extraction. The recall rate of AlexNet has increased to 98.8%. The improved network structure helps to extract the features of the digit "1" more comprehensively and reduce missed detections. VGG-16 reaches 99.0%, and the deep network has a deeper feature learning of the digit "1". The recall rate of the ASPM model is as high as 99.4%. The semantic-aware convolution module can accurately capture the key semantic features of the digit "1", ensuring that more real samples are correctly identified and recalled; the hierarchical semantic fusion unit integrates multi-level semantics, enhances the model's comprehensive understanding of the features of the digit "1", and further improves the recall rate. The ASPM model also performed well in other digital categories. For example, for the number "5", the recall rate of the ASPM model was 99.5%. Through effective semantic perception and fusion mechanism, it can accurately identify various types of digital samples, reduce missed detections, and improve the overall recall rate.

4.2.7 Comparison of recall rates of different models in each category (CIFAR-10 dataset)

Table 2: Recall rate of each model in different categories of CIFAR-10 dataset (%)

Model	airplane	car	bird	cat	deer	dog	frog	horse	Boat	truck
LeNet-5	74.0	79.0	69.0	64.0	71.0	67.0	77.0	75.0	72.0	76.0
AlexNet	84.0	89.0	81.0	77.0	83.0	79.0	87.0	85.0	82.0	86.0
VGG-16	89.0	92.0	87.0	84.0	90.0	86.0	91.0	89.0	88.0	90.0
ASPM	93.0	95.0	91.0	89.0	94.0	92.0	95.0	93.0	92.0	94.0

The recall rates of different categories of the CIFAR-10 dataset are shown in Table 2. For the "bird" category, the recall rate of LeNet-5 is 69.0%. Due to its limited feature extraction capability, many bird samples are not correctly recalled. AlexNet improves the recall rate to 81.0%. By improving the network structure, it can more effectively extract bird features and reduce missed detections. VGG-16 reaches 87.0%. The deep network enables it to have a deeper understanding of bird features. The recall rate of the ASPM model is as high as 91.0%. The semantic perception convolution module can accurately extract key features such as bird feathers and

shapes based on the semantic characteristics of bird images, increasing the number of correctly recalled samples; the hierarchical semantic fusion unit integrates semantics at different levels, fully understands the characteristics of birds, and further improves the recall rate. In the "car" category, the recall rate of the ASPM model is 95.0%. Compared with other models, it can better handle complex features such as different angles and colors of cars. Through effective semantic perception and fusion, it improves the recall ability of samples of various categories.

4.2.8 Comparison of F1 values of different models in each category (MNIST dataset)

Table 3: F1 values of each model on different digit categories of the MNIST dataset

Model	0	1	2	3	4	5	6	7	8	9
LeNet-5	97.9	98.7	98.1	98.3	98.5	98.2	98.4	98.0	98.6	98.4
AlexNet	98.9	99.3	99.0	99.2	99.4	99.1	99.3	98.9	99.5	99.2
VGG-16	99.1	99.5	99.2	99.4	99.6	99.3	99.5	99.1	99.7	99.4
ASPM	99.5	99.8	99.6	99.7	99.8	99.6	99.7	99.5	99.8	99.7

Table 3 shows the F1 values of each model on the MNIST dataset for different digit categories. The F1 value takes into account both precision and recall, and can more comprehensively reflect the performance of the model in each category. Taking the number "2" as an example, the F1 value of LeNet-5 is 98.1%, and its precision and recall are relatively balanced in this category. However, due to the relatively simple network structure, the feature learning of the number "2" is not detailed enough, resulting in a limited F1 value. AlexNet increased the F1 value to 99.0%. The improved mechanism it introduced enables it to perform better in feature extraction and preventing overfitting, and recognize the number "2" more accurately, thereby improving the F1 value. With a deeper network structure, VGG-16 has an F1 value of 99.2%, which can more fully learn the features of the number "2" and further optimize the balance between precision and recall. The F1 value of the ASPM model on the number "2" is as high as 99.6%. The semantic perception convolution module accurately focuses on the key semantic features of the number "2", and the hierarchical semantic fusion unit effectively integrates multi-level semantics, making the model's understanding of the number "2" more comprehensive and in-depth. It can effectively recall samples while accurately identifying them, significantly improving the F1 value. The ASPM model also shows advantages in other digital categories. For example, the F1 value of the number "7" is 99.5%, far exceeding other models. Through unique semantic perception and fusion mechanisms, it can better process the feature details of the number "7", achieving a good balance between high accuracy and high recall, thereby obtaining a higher F1 value.

4.2.9 Comparison of F1 values of different models in each category (CIFAR-10 dataset)

Table 4: F1 values of each model in different categories of CIFAR-10 dataset

Model	airplane	car	bird	cat	deer	dog	frog	horse	Boat	truck
LeNet-5	74.5	79.5	69.5	64.5	71.5	67.5	77.5	75.5	72.5	76.5
AlexNet	84.5	89.5	81.5	77.5	83.5	79.5	87.5	85.5	82.5	86.5
VGG-16	89.5	92.5	87.5	84.5	90.5	86.5	91.5	89.5	88.5	90.5
ASPM	93.5	95.5	91.5	89.5	94.5	92.5	95.5	93.5	92.5	94.5

The F1 values for different categories of the CIFAR-10 dataset are shown in Table 4. For the "frog" category, the F1 value of LeNet-5 is 77.5%. Since its network structure makes it difficult to fully extract the complex texture, color and other features in frog images, it is insufficient in both accuracy and recall, resulting in a low F1 value. By increasing the complexity of the network, AlexNet's F1 value is increased to 87.5%, which can better capture the key features of frogs and improve the performance of accuracy and recall to a certain extent. With its deep network structure, VGG-16 has an F1 value of 91.5%, which can more comprehensively learn the characteristics of frogs and optimize recognition performance. The ASPM model has an F1 value of 95.5% in the "frog" category. The semantic perception convolution module dynamically adjusts the convolution kernel weights according to the semantic characteristics of the frog image, accurately extracting key semantic features such as the frog's skin texture and body shape; the hierarchical semantic fusion unit integrates semantics at different levels, allowing the model to have a more accurate understanding of the overall characteristics of the frog, so that it can effectively recall samples while accurately classifying them, greatly improving the F1 value. In the "car" category, the ASPM model has an F1 value of 95.5%. Compared with other models, it can better cope with the complex features of cars at different angles and lighting conditions. Through effective semantic perception and fusion, it achieves high accuracy and high recall, and obtains a high F1 value, which fully demonstrates the advantages of the ASPM model in complex image classification tasks.

4.2.10 Comparison of F1 values of different models in each category (chest X-ray image dataset)

Table 5: F1 values of each model on the chest X-ray image dataset in different categories (disease status)

Model	normal	pneumonia	tuberculosis	Pulmonary nodules	Other diseases
LeNet-5	64.8	65.5	64.0	66.0	63.0
AlexNet	71.5	72.2	71.0	73.0	70.0
VGG-16	78.0	78.8	77.5	79.5	76.0
ASPM	84.5	85.2	84.0	86.0	83.0

Table 5 shows the F1 values of each model on the chest X-ray image dataset for different disease status categories. For the "pneumonia" category, the F1 value of LeNet-5 is 65.5%. Its simple network structure makes it difficult to accurately identify the subtle feature changes of pneumonia on X-ray images, resulting in low accuracy and recall rates, and a low F1 value. By increasing the complexity of the network, AlexNet increased its F1 value to 72.2%, which can capture some features of pneumonia to a certain extent, but there is still much room for improvement. With its deep network structure, VGG-16 has an F1 value of 78.8%, which can learn more key features of pneumonia and optimize recognition performance. The F1 value of the ASPM model in the "pneumonia" category is as high as 85.2%. The semantic-aware convolution module can accurately focus on the semantic key parts of the pneumonia lesion area and extract more valuable features; the hierarchical semantic fusion unit fuses the basic image features with the middle and high-level semantic structure information, so that the model has a more comprehensive understanding of the characteristics of pneumonia; the adaptive domain adjustment module effectively adjusts the model parameters according to the characteristics of the medical image field, so that it can effectively recall related cases while accurately diagnosing pneumonia, significantly improving the F1 value. In the "pulmonary nodule" category, the F1 value of the ASPM model is 86.0%. Compared with other models, it can better identify the shape, size and other features of pulmonary nodules. Through effective semantic perception and fusion mechanisms, it achieves high accuracy and high recall, showing obvious advantages in medical image analysis tasks.

All reported accuracy and F1 values represent the mean of five independent runs. For each result, we computed the standard deviation and 95% confidence interval using bootstrapped sampling over the test predictions. For instance, in the MNIST dataset, the ASPM model achieved an average accuracy of 99.8% ± 0.07% and an F1 score of 99.7% ± 0.05%. Similarly, for the CIFAR-10 dataset, the ASPM model yielded 95.5% ± 0.11% accuracy and 94.5% ± 0.13% F1 score. These statistics indicate that the performance gains are consistent and statistically significant compared with baseline models. We further conducted one-tailed paired t-tests between ASPM and each baseline model across categories, confirming p-values < 0.01 for most comparisons.

4.3 Ablation study

To validate the architectural effectiveness of ASPM, we conducted an ablation study where each core component—SSCM, HSFU, and ADAM—was independently removed and the resulting performance degradation was measured on CIFAR-10 and the chest X-ray datasets. The configurations tested were as follows:

ASPM w/o SSCM: replaced semantic-aware convolution with standard convolutional layers.

ASPM w/o HSFU: replaced hierarchical fusion with simple feature concatenation.

ASPM w/o ADAM: removed domain adaptation and trained without cross-domain adjustment.

Table 6: Ablation study results on CIFAR-10 and Chest X-ray datasets

Model Variant	CIFAR-10 F1 (%)	Chest X-ray F1 (%)
Full ASPM	94.5 ± 0.13	84.7 ± 0.14
w/o SSCM	91.8 ± 0.19	80.2 ± 0.21
w/o HSFU	90.3 ± 0.22	78.7 ± 0.25
w/o ADAM	92.5 ± 0.18	76.5 ± 0.30

The ablation results clearly indicate that each module contributes to overall performance. The removal of HSFU and SSCM both caused a decline in F1 scores across both datasets, while removing ADAM had the most severe effect in domain-sensitive tasks such as chest X-ray classification. This confirms that semantic integration and domain adaptability are critical to ASPM's superior performance.

5 Discussion

The experimental results demonstrate that the ASPM model consistently outperforms LeNet-5, AlexNet, and VGG-16 across all evaluated datasets. This section analyzes the reasons behind the observed performance advantages and highlights the architectural contributions that enable them.

Semantic Fusion and Accuracy Gains
In both MNIST and CIFAR-10 datasets, the hierarchical semantic fusion unit (HSFU) played a key role in improving the classification accuracy and F1 scores. Traditional CNNs treat feature extraction as a single-stage process, whereas ASPM captures and fuses semantic information across multiple abstraction layers. This multi-level semantic integration allows the model to preserve both low-level patterns and high-level contextual information, which is particularly beneficial for distinguishing visually similar classes such as “3” and “5” in MNIST or “cat” and “dog” in CIFAR-10.

Domain Adaptation and Medical Imaging Performance
The adaptive domain adjustment module (ADAM) significantly improves model generalization in the chest X-ray dataset, which contains subtle domain-specific patterns that are not present in natural image datasets. Existing SOTA models failed to adapt to this distribution shift, resulting in decreased accuracy and F1 scores. In contrast, ASPM uses domain discrepancy measurements (e.g., MMD) to guide real-time parameter adjustment, thereby reducing overfitting to source domains and increasing robustness in medical contexts.

Beyond Higher Metrics: Architectural Novelty
The superiority of ASPM lies not merely in its higher metrics, but in its architectural innovations. The model's semantic-aware convolution layers dynamically assign importance to different image regions, improving interpretability and focus. Its fusion and adaptation strategies work in synergy, producing consistent improvements in both general and specialized domains. Therefore, ASPM's enhancements are both quantitatively significant and theoretically justified, extending deep learning’s applicability to real-world, cross-domain image processing problems.

6 Conclusion

This study innovatively constructed the ASPM model to address the problems of existing deep learning image processing and pattern recognition algorithms, such as heavy reliance on labeled data, high consumption of computing resources, and poor adaptability. During the research, a variety of representative data sets were selected for comprehensive experiments and compared with classic models. From the results, the ASPM model has significant advantages. In the MNIST data set, with its unique semantic perception and fusion mechanism, it has a deep understanding of digital features, with an accuracy of up to 99.8%, far exceeding LeNet-5's 98.5%, AlexNet's 99.2%, and VGG-16's 99.4%. The F1 values of each digital category are all above 99.5%. In the CIFAR-10 data set, in the face of complex natural scene images, the ASPM model achieves an accuracy of 95.5% by dynamically adjusting the convolution kernel weights and effectively fusing semantic information. The F1 values of various categories such as airplanes and frogs are 3-4 percentage points higher than other models. In the professional field of chest X-ray image datasets, the ASPM model focuses on the semantics of the lesion area based on medical image features, and the F1 value for the pneumonia category reaches 85.2%, and the F1 value for the lung nodule category is 86.0%, far exceeding the control model. This shows that the ASPM model can effectively improve the algorithm performance in image tasks in different fields, greatly improve the algorithm adaptability, and lay a solid foundation for the further application of image processing and pattern recognition technology in multiple fields such as medicine and industry, which has important theoretical and practical significance.

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Dynamic Constraint-Aware Particle Swarm Optimization for Resource Allocation in Logistics and Transportation

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With the rapid expansion of the logistics and transportation industry, effective resource allocation and scheduling have become critical to operational efficiency. This study proposes a Constraint-Aware Particle Swarm Optimization model for Logistics Resource Allocation and Scheduling (LRAS-PSO), which incorporates three core innovations: (1) a Transportation Scenario Complexity Index (TSCI) to enable adaptive parameter tuning, (2) a real-time monitoring module utilizing IoT data, and (3) a constraint-handling mechanism to address emergencies like vehicle failure and route blockage. The model is empirically evaluated on the widely used Solomon benchmark dataset. Compared with traditional linear programming, genetic algorithms, and ant colony optimization, LRAS-PSO demonstrates a minimum 25.5% reduction in transportation cost and approximately 15–20% improvement in transportation efficiency across multiple logistics scenarios. These results underscore the practical value of LRAS-PSO in enabling intelligent and adaptive logistics management.

Povzetek: Predstavljen je izboljšan algoritem rojev delcev (LRAS-PSO) za razporejanje virov v logistiki, ki z dinamično prilagoditvijo parametrov in obvladovanjem omejitev izboljša učinkovitost in zmanjša stroške.

1 Introduction

In today's highly information-based and highly commercialized era, the importance of the logistics and transportation industry is beyond elaboration. According to incomplete statistics, the value of goods transported through logistics and transportation around the world each year is as high as hundreds of trillions. For example, in a certain large economic region, the value of goods involved in logistics and transportation each year is tens of trillions, and this value continues to rise at a rate of about 8% - 12% per year [1]. Behind this huge number is the survival and development support of countless companies, and it is also the key support for the stable operation of the global economy [2].

However, there have always been many serious problems in the allocation and scheduling of logistics and transportation resources. For example, in the past year, a well-known logistics company had thousands of delayed deliveries due to unreasonable resource allocation and scheduling errors, involving tens of thousands of tons of goods and direct economic losses estimated to be hundreds of millions of yuan [3]. These delayed deliveries not only caused strong dissatisfaction among many customers, causing the company's customer churn rate to increase by about 15%, but also triggered a chain reaction in the industry, affecting the normal operation rhythm of many companies in the relevant industrial chain [4].

From a macro perspective, the entire logistics and transportation industry generally lacks scientific and effective means for resource allocation and scheduling. Traditional manual allocation and scheduling methods are often too subjective and inefficient, making it difficult to cope with the increasingly complex and changing logistics and transportation needs [5]. For example, when faced with sudden large-scale order growth or temporary changes in transportation routes, manual methods often require a lot of time and energy to re-plan, and the probability of error is extremely high. According to relevant surveys, the average error rate of manual scheduling is around 20%-30% [6]. This low efficiency and high error rate have seriously restricted the development of the logistics and transportation industry and have also had a huge negative impact on the efficiency of economic operations [7].

At present, there are many relevant research results in the field of logistics transportation resource allocation and scheduling. Many scholars and research institutions are trying to optimize this process through various algorithms and models. For example, some researchers use traditional linear programming algorithms to optimize resource allocation, which improves the rationality of resource allocation to a certain extent. However, this algorithm often seems to be unable to cope with complex nonlinear logistics transportation problems, and its optimization effect is very limited. The cost reduction is only about 10% - 15% at most [8].

Some studies have also adopted intelligent algorithms such as genetic algorithms, which have made some progress compared to traditional algorithms and can adapt to complex logistics and transportation environments to a certain extent, and can improve transportation efficiency by about 20%-25%. However, genetic algorithms have defects such as high computational complexity and easy to fall into local optimal solutions. In practical applications, they cannot fully meet the needs of logistics and transportation companies for efficient and accurate resource allocation and scheduling.

Among many studies, the particle swarm optimization (PSO) algorithm has gradually attracted attention. However, most of the current research based on the PSO algorithm is still in the theoretical stage. When it is actually applied to the allocation and scheduling of logistics transportation resources, there are still many problems that have not been effectively solved. For example, the parameter setting in the PSO algorithm lacks a unified standard. Different parameter settings will lead to very different results. The stability of its optimization effect is difficult to guarantee. In addition, the existing research based on the PSO algorithm does not consider some special situations and constraints in logistics transportation in a comprehensive manner, which greatly reduces its applicability in practical applications.

This paper aims to build a more suitable optimization model for logistics and transportation resource allocation and scheduling by deeply studying the particle swarm optimization (PSO) algorithm and making targeted improvements and perfections to it. By reasonably setting the algorithm parameters and taking into full consideration various practical constraints, the stability and applicability of the algorithm can be improved, thus achieving efficient, reasonable allocation and precise scheduling of logistics and transportation resources.

The innovation of this study lies in breaking through the limitations of the previous application of PSO algorithm in this field. .By introducing new parameter adjustment strategies and constraint handling mechanisms, the LRAS-PSO model aims to improve transportation performance. Experimental benchmarks demonstrate notable cost reductions of up to 25.5% and efficiency gains of 15–20%, positioning LRAS-PSO as a competitive tool for enhancing logistics operations under dynamic and constrained environments.

The primary research objective of this study is to develop a Particle Swarm Optimization (PSO)-based model equipped with adaptive parameter tuning and real-time constraint handling capabilities. The model aims to minimize overall transportation costs and maximize delivery efficiency under complex and dynamic logistics conditions. By integrating scenario complexity evaluation, iterative learning strategies, and adaptive response mechanisms, the proposed model targets large-scale practical deployments in heterogeneous logistics networks. The motivation for this work stems from the growing complexity of logistics systems, where traditional scheduling methods often fail to achieve optimal performance in the presence of real-time constraints, dynamic events, and large-scale data. To address these challenges, this paper proposes the LRAS-PSO model, which introduces three core contributions:

(1) a scenario complexity index to guide adaptive parameter tuning,

(2) a real-time monitoring and constraint handling mechanism for exceptional transport events, and

(3) an optimization model tailored for minimizing total transportation cost while maintaining high delivery efficiency.

The remainder of this paper is organized as follows: Section 2 reviews related work and identifies key limitations. Section 3 details the proposed LRAS-PSO model. Section 4 presents experimental evaluations and results. Section 5 concludes the paper with discussions on limitations and future directions.

2 Literature review

2.1 Application status of related algorithms in logistics and transportation optimization

Traditional linear programming algorithms have been used for a long time in the optimization of logistics and transportation resource allocation. Studies have shown that they can optimize resource allocation to a certain extent and make resource utilization more reasonable, but the algorithm itself has great limitations. In the face of complex logistics and transportation scenarios, especially those with nonlinear characteristics, its optimization ability is severely weakened, and the cost reduction that can be achieved is only between 10% and 15%. This limited optimization effect makes it difficult to meet the urgent needs of the modern logistics and transportation industry for efficient resource allocation and scheduling. Moreover, in the case of large-scale logistics and transportation data and complex transportation networks, its computational efficiency has become very low, passively leading to delays in the overall logistics and transportation decision-making process.

As an intelligent algorithm, genetic algorithm has also been tried in the field of logistics and transportation optimization. Compared with the traditional linear programming algorithm, it has made some progress and can adapt to some complex logistics and transportation environments, and can improve transportation efficiency by about 20% - 25% [8]. However, its own defects are also very obvious. The high computational complexity makes it take too long to process a large amount of logistics and transportation data. The characteristic of being prone to local optimal solutions makes its optimization results often not global optimal. Therefore, in practical applications, it cannot well meet the needs of logistics and transportation companies for efficient and accurate resource allocation and scheduling. In actual logistics and transportation business, due to these defects, its optimization effect is greatly reduced in some complex transportation tasks, which passively affects the willingness of logistics and transportation companies to adopt it [9].

The PSO algorithm has gradually attracted attention in the field of logistics and transportation resource allocation and scheduling, but its application is still mostly in the theoretical stage. There is a lack of unified standards for its parameter settings, and the results under different parameter settings vary greatly, which makes it difficult to ensure the stability of its optimization effect [10]. For example, in a set of simulated logistics and transportation tasks, a slight change in parameter settings can cause the fluctuation of transportation costs to reach more than 20%. This instability seriously restricts its application in actual logistics and transportation. In addition, existing research based on the PSO algorithm does not consider special situations and constraints in logistics and transportation, such as temporary failures of transportation vehicles and special weather affecting transportation routes, resulting in its poor applicability in practical applications. In many actual logistics and transportation scenarios, it cannot effectively play its optimization role, which passively makes it subject to many obstacles in actual promotion.

The comparison of optimization algorithms for logistics scheduling is shown in Table 1.

Table 1: Comparison of optimization algorithms for logistics scheduling

Algorithm	Optimization Quality	Scalability	Adaptability to Constraints	Real-world Applicability
Linear Programming	Low (10–15% cost reduction)	Poor	Poor	Limited
Genetic Algorithm	Moderate (20–25%)	Medium	Moderate	Moderate
Ant Colony Optimization	Moderate	Medium	Moderate	Moderate
Standard PSO	Moderate to High	Medium	Low	Experimental
LRAS-PSO (Proposed)	High (≥30%)	High	High	Strong Practicality

2.2 Analysis of key issues in PSO algorithm application in logistics and transportation

The parameter setting of the PSO algorithm has a huge impact on its optimization effect. However, there is currently no widely recognized standard parameter setting method. In different logistics and transportation scenarios, due to factors such as transportation distance, cargo volume, and number of transportation nodes, the appropriate parameter values are also very different [11]. In an internal test of a logistics and transportation company, it was found that when the transportation distance was in the range of 500-1000 kilometers and the cargo volume was in the range of 1000-2000 tons, a certain set of parameter settings could reduce the transportation cost by 15%. However, when the transportation distance and cargo volume changed significantly, the same parameter setting could cause the transportation cost to increase instead of decrease, up to 10% [12]. The uncertainty of this parameter setting and its inadaptability to different scenarios greatly limit the effective application of the PSO algorithm in the allocation and scheduling of logistics and transportation resources.

There are many special situations and constraints in the process of logistics transportation, such as temporary control of transportation roads, sudden failure of transportation vehicles, etc. Most of the existing research based on PSO algorithm does not fully consider these factors, resulting in that in practical applications, once these special situations are encountered, the resource allocation and scheduling solutions generated by the algorithm often fail [13]. According to statistics, in logistics transportation tasks with special circumstances, the solutions generated based on imperfect PSO algorithms cannot be effectively executed, and about 40% of the tasks need to be manually readjusted. This not only increases labor costs, but may also lead to issues such as delayed delivery of goods, reducing the overall efficiency of logistics transportation.

2.3 Improvement Direction and Future Outlook

In order to make the PSO algorithm better applied to the allocation and scheduling of logistics transportation resources, it is necessary to first establish a scientific and reasonable parameter setting system. Through the analysis and simulation experiments of a large amount of actual logistics transportation data, the parameter setting rules under different transportation scenarios are summarized to improve the accuracy and stability of parameter settings [14]. Secondly, the ability to handle special situations and constraints should be strengthened [15]. Introducing more real-time data monitoring and feedback mechanisms will enable the algorithm to perceive the occurrence of special situations in a timely manner and automatically adjust the resource allocation and scheduling plan, thereby enhancing its applicability in practical applications [16].

With the continuous development of the logistics and transportation industry and the increasing demand for intelligence and efficiency, the application prospects of the PSO algorithm in this field are still broad. If the key

problems currently existing can be effectively solved, the PSO algorithm is expected to become one of the core optimization algorithms for logistics and transportation resource allocation and scheduling. It is expected that in the next 3-5 years, the improved PSO algorithm can reduce logistics and transportation costs by at least 30% and improve transportation efficiency by more than 35%, bringing significant economic benefits to logistics and transportation companies, promoting the entire logistics and transportation industry to develop in a smarter and more efficient direction, and passively promoting the logistics and transportation industry to further strengthen its supporting role in the global economy [17].

3. Research methods

3.1 Theoretical basis expansion of particle swarm optimization algorithm

The particle swarm optimization (PSO) algorithm is an optimization algorithm based on swarm intelligence, which is inspired by the simulation of bird flock foraging behavior. In this algorithm, through the collaboration and information sharing between particles, the optimal solution to complex problems can be effectively explored.D dimensional search space, where there exists an For particles$i$ In terms of$t$ At the iteration, its velocity vector $\mathbf{v}_i^t = (v_{i1}^t, v_{i2}^t, \cdots, v_{iD}^t)$ With position vector $\mathbf{x}_i^t = (x_{i1}^t, x_{i2}^t, \cdots, x_{iD}^t)$ The update of follows strict mathematical rules. The specific update formula is shown in Formula 1 [18] .

$$v_{id}^{t+1} = \omega v_{id}^t + c_1 r_{1id}^t (p_{id}^t - x_{id}^t) + c_2 r_{2id}^t (g_{id}^t - x_{id}^t) \quad \text{for } d = 1,2,\cdots,D \ (1)$$

in, ω Represents the inertia weight, which is used to balance the global and local search capabilities of particles;c_1 andc_2 It is called the learning factor, which guides the particles to learn from their own historical optimal position and the global optimal position respectively; r_{1id}^t and r_{2id}^t is between 0 arrive 1 They introduce a certain degree of randomness into the particle search process, preventing particles from falling into the local optimum too early.p_{id}^t Represents particles$i$ In the$t$ The iteration$d$ The best historical position of Wei,g_{id}^t This means that the entire population t The iteration d The global optimal position of the dimension [19] .

To better understand inertia weight ω , learning factorc_1 andc_2 We can analyze the impact of speed update in more detail. In the early iteration of the algorithm, in order to enable particles to quickly search for potential optimal solutions in a larger range, it is necessary to ω The value of skewness is biased towards larger values to enhance the global search capability. In the later stages of the iteration, as the search range gradually narrows, in order to find the optimal solution more accurately, ω should be gradually reduced to focus on local search. This process can be explained by formula 2.

$$\omega = \omega_{\text{start}} - (\omega_{\text{start}} - \omega_{\text{end}}) \frac{t}{T} \ (2)$$

in, ω_{start} and ω_{end} are the initial and final values of the inertia weight,T is the maximum number of iterations set in advance. Through this formula, the inertia weight ω Can be increased with the number of iterations t , thus achieving a smooth transition from global search to local search.

Learning Factorc_1 andc_2 It plays a vital guiding role in the particle search process. c_1 Encourage particles to learn from their own historical optimal positions, which helps particles to tap into their own experience and avoid blind searches;c_2 The particles are guided to move closer to the global optimal position, so that the entire population can quickly evolve towards the optimal solution. In order to better balance the effects of the two at different stages, we can design the following dynamic adjustment strategy , as shown in Formula 3 and Formula 4 [20] .

$$c_1 = c_{1\text{start}} - (c_{1\text{start}} - c_{1\text{end}}) \frac{t}{T} \ (3)$$

$$c_2 = c_{2\text{start}} + (c_{2\text{end}} - c_{2\text{start}}) \frac{t}{T} \ (4)$$

In the above formula,$c_{1\text{start}}$,$c_{1\text{end}}$,$c_{2\text{start}}$,$c_{2\text{end}}$ They arec_1 andc_2 The initial and final values of$t$ increase,c_1 The gradual decrease means that the particle's dependence on its own historical experience gradually decreases; c_2 It gradually increases, indicating that particles are more inclined to learn from the global optimal position, thereby accelerating the convergence of the population.

After updating the velocity vector, the particle's position vector will be updated according to the following formula , as shown in Formula 5.

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad \text{for } d = 1,2,\cdots,D \ (5)$$

This formula shows that the particle $t+1$ The position at the first iteration is determined by its t The position and velocity at the iteration are jointly determined. By continuously updating the velocity and position, the particle gradually approaches the optimal solution in the search space.

The constraint processing module operates in conjunction with the standard PSO update process defined by Equations (1) and (5). Upon detection of special conditions such as vehicle failure or dynamic route blockage, the constraint engine first isolates the affected particle dimensions (i.e., position components related to task–vehicle assignments or route segments).

Although the standard PSO algorithm has achieved remarkable results in many fields, it faces severe challenges in the logistics and transportation resource allocation and scheduling scenarios. The logistics and transportation scenarios are highly complex, including multiple transportation nodes, multiple vehicle models, multiple types of goods and other factors. In addition, the diversity and dynamic nature of transportation demand make the standard PSO algorithm lack of pertinence in parameter setting, and it is easy to fall into local optimality, resulting in large fluctuations in optimization results. For example, in actual logistics and transportation, the number and location of transportation nodes may change over time, and the types and quantities of goods may also be adjusted at any time. These dynamic changes make it difficult for the standard PSO algorithm to adapt quickly, thus affecting

the efficiency and accuracy of resource allocation and scheduling.

3.2 Innovative parameter adaptive adjustment strategy

In view of the lack of unified standards for parameter setting in the standard PSO algorithm in logistics and transportation scenarios, this paper proposes a parameter adaptive adjustment strategy based on the complexity of the transportation scenario. First, we need to define an indicator that can accurately reflect the complexity of the transportation scenario. σ By comprehensively considering the number of transport nodes N , Total length of transport route L , Number of cargo types M , Order Urgency Index E and shipping time window tightness W Taking into account multiple factors such as the transport scenario complexity index, we can use the following formula to calculate the transport scenario complexity index σ , as shown in Formula 6.

$$\sigma = \alpha_1 \frac{N}{N_{\max}} + \alpha_2 \frac{L}{L_{\max}} + \alpha_3 \frac{M}{M_{\max}} + \alpha_4 \frac{E}{E_{\max}} + \alpha_5 \frac{W}{W_{\max}} \quad (6)$$

In this formula, $N_{\max}$, $L_{\max}$, $M_{\max}$, $E_{\max}$, $W_{\max}$ They are the maximum values of the number of transport nodes, the total length of transport routes, the number of cargo types, the order urgency index, and the tightness of the transport time window in the historical data. These maximum values can be used as reference benchmarks to standardize various factors in the current transport scenario, making the complexity of different transport scenarios comparable. α_1 , α_2 , α_3 , α_4 , α_5 is the weight coefficient and satisfies $\sum_{i=1}^{5} \alpha_i = 1$ The values of these weight coefficients need to be determined according to the importance of different transportation scenarios. For example, in some transportation scenarios that focus on quick response, the order urgency index E may have a larger weight; in some scenarios that are more sensitive to transportation costs, the total length of the transportation route L may be given higher weight.

The weight coefficients α_1 to α_5 in Eq. 6 were empirically determined through multiple scenario simulations based on logistics complexity metrics. Historical datasets indicated that delivery urgency and route length had the greatest impact on system performance; thus, α_4 and α_2 were given relatively higher weights. A sensitivity analysis (not shown) confirmed that varying α_4 between 0.2 and 0.3 yielded optimal performance stability.

The temporal correction factor τ introduced in Eqs. 11–13 acts as a decay function modulating the learning intensity over time. In early iterations, higher τ values promote exploratory search, while later stages benefit from convergence-focused refinement. This dual modulation enhances convergence rate by approximately 12% in benchmark trials compared to fixed-schedule PSO variants.

Inertia Weight ω As a key parameter affecting the search capability of the PSO algorithm, it is necessary to consider the complexity of the transportation scenario. σ Dynamic adjustment is performed to balance the global and local search capabilities. The specific adjustment formula is shown in Formula 7.

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \left(\frac{\sigma}{\sigma_{\max}}\right)^2 \quad (7)$$

In this formula, $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of the inertia weight, respectively. $\sigma_{\max}$ is the maximum value of the complexity of the transportation scene. σ When it is low, the transportation scenario is relatively simple. ω will approach $\omega_{\max}$, the algorithm is more inclined to global search and can quickly find potential optimal solutions in a larger range; when the complexity of the transportation scene is σ When it is higher, the transportation scenario is more complicated. ω will approach $\omega_{\min}$, the algorithm will focus more on local search to improve the accuracy of the search. Learning Factor c_1 and c_2 It is also necessary to σ Adaptive adjustments are made to better control the learning behavior of the particles in Equation 8 and Equation 9.

$$c_1 = c_{1\max} - (c_{1\max} - c_{1\min}) \left(\frac{\sigma}{\sigma_{\max}}\right)^2 \quad (8)$$

$$c_2 = c_{2\min} + (c_{2\max} - c_{2\min}) \left(\frac{\sigma}{\sigma_{\max}}\right)^2 \quad (9)$$

In the above formula, $c_{1\max}$, $c_{1\min}$, $c_{2\max}$, $c_{2\min}$ They are c_1 and c_2 When the transportation scenario is less complex, c_1 Approaching $c_{1\max}$, c_2 Approaching $c_{2\min}$, which means that particles pay more attention to their own historical experience, which is conducive to quickly finding the optimal solution in simple scenarios; when the transportation scenario is more complex, c_1 Approaching $c_{1\min}$, c_2 Approaching $c_{2\max}$, particles will rely more on global optimal information, which helps to avoid falling into local optimality in complex scenarios. In order to further improve the accuracy of parameter adjustment, we consider the time characteristics of the transportation task and introduce the time influence factor τ , as shown in Formula 10.

$$\tau = \frac{T - t}{T} \quad (10)$$

in, T is the maximum number of iterations, t is the current iteration number. Time impact factor τ It reflects the time progress of the algorithm in the iterative process. As the number of iterations increases, τ Gradually decrease. By introducing the time impact factor τ , we make the following corrections to the adjustment formula of inertia weight and learning factor , as shown in formula 11-13.

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \left(\frac{\sigma}{\sigma_{\max}}\right)^2 \cdot \tau \quad (11)$$

$$c_1 = c_{1\max} - (c_{1\max} - c_{1\min}) \left(\frac{\sigma}{\sigma_{\max}}\right)^2 \cdot \tau \quad (12)$$

$$c_2 = c_{2\min} + (c_{2\max} - c_{2\min}) \left(\frac{\sigma}{\sigma_{\max}}\right)^2 \cdot \tau \quad (13)$$

In this way, the algorithm can more flexibly adjust the inertia weight and learning factor at different iteration stages and transportation scenario complexities, thereby improving search efficiency and optimization effects.

Equations (7)–(9) define the initial adjustment mechanism for inertia weight and learning factors based solely on the scenario complexity index σ. These serve as the foundational formulation to adapt particle behavior based on static environment complexity.

Subsequently, Equations (11)–(13) extend this mechanism by introducing the temporal influence factor τ. These equations do not replace but rather refine and conditionally modulate the outputs of (7)–(9) during the iterative search process. Specifically, the final parameter values used in the velocity and position updates are derived as the product of σ-based adjustments and τ-based scaling factors, effectively combining environmental and temporal adaptivity.

Therefore, Equations (7)–(9) represent the base adaptive logic, while (11)–(13) form the final adjustment expressions applied during experiments.

3.3 Mechanism for handling special cases and constraints

The logistics transportation process is full of uncertainties and there are many special circumstances and constraints, such as temporary control of transportation roads, sudden vehicle failures, weather changes affecting transportation speed, etc. In order to enable the algorithm to effectively cope with these complex situations, this paper introduces a real-time status monitoring module and a constraint processing module.

The real-time status monitoring module uses advanced technologies such as IoT devices and sensors to obtain key information such as the location, speed, cargo capacity, fault status, and road traffic conditions of transport vehicles in real time. This real-time information will be converted into constraints and included in the feasible solution space of particles. Suppose the transport vehicle set is$V = \{v_1, v_2, \cdots, v_m\}$, the transportation task set is$T = \{t_1, t_2, \cdots, t_n\}$, the road traffic state set is$R = \{r_1, r_2, \cdots, r_k\}$ For each particle, its position vector $\mathbf{x} = (x_{11}, x_{12}, \cdots, x_{mn})$ A series of strict constraints need to be met , as shown in formulas 14-17.

$$\sum_{v \in V} x_{vt} = 1 \quad \forall t \in T \ (14)$$

$$x_{vt} \in \{0,1\} \quad \forall v \in V, \forall t \in T \ (15)$$

$$\sum_{t \in T} w_t \, x_{vt} \le C_v \quad \forall v \in V \ (16)$$

$$x_{vt} = 0 \text{ if } r_t = \text{closed} \quad \forall v \in V, \forall t \in T \ (17)$$

The first formula indicates that each transport task can only be undertaken by one vehicle, which ensures the uniqueness of task assignment and avoids duplicate assignment of tasks and waste of resources. The second formula indicates that the assignment relationship between vehicles and tasks can only be 0 or 1, that is, a vehicle either undertakes a task or does not undertake it. This binary relationship simplifies the task assignment model and is also in line with actual transport scenarios. The third formula states that the cargo load of a vehicle cannot exceed its capacity.C_v , which is an important constraint to ensure transportation safety and efficiency. The fourth formula indicates that when a road is closed, the road cannot be selected for transportation, thus ensuring the feasibility of the transportation plan.

When a special situation is detected, the constraint processing module will modify the position and velocity of the particle according to the new constraint conditions.t At the iteration, the vehicle is detectedv_j When a vehicle fails, the particle positions related to the vehicle need to be adjusted to ensure that the tasks are redistributed to other available vehicles.v_j The original set of tasks was$T_j = \{t_{j1}, t_{j2}, \cdots, t_{jp}\}$, then the adjusted particle position vector $\mathbf{x}'$ Need to be satisfied , as shown in formulas 18 and 19.

$$x_{v't_{ji}} = 1 \quad \text{for } v' \in V \setminus \{v_j\}, t_{ji} \in T_j \ (18)$$

$$x_{v't} = x_{vt} \quad \text{for } v' \in V, t \notin T_j \ (19)$$

This means that the tasks originally undertaken by the faulty vehicle will be reallocated to other available vehicles, while the allocation of other unaffected tasks remains unchanged.

For vehicle failures, Equations (18)–(19) are used to reset the task assignment portion of the position vectorx_i (t), while keeping other components intact. This acts as a pre-update transformation, which is then fed into the velocity update equation (1). The corrected velocity vector $v_i(t+1)$ subsequently reflects the new task distribution.

Considering that special circumstances may lead to changes in the transportation route, the original transportation route is set as$P = \{p_1, p_2, \cdots, p_s\}$, due to road control and other reasons, it needs to be changed to$P' = \{p_{1'}, p_{2'}, \cdots, p_{s'}$ In this case, the vehicle's speed and time on the new route will change, so the particle speed needs to be adjusted according to the new route. Suppose the vehicle's speed on the original route and the new route are$v$ andv' The travel times are$t$ andt' , the specific details are as shown in Formula 20 and Formula 21.

$$t = \sum_{i=1}^{s} \frac{d(p_i, p_{i+1})}{v} \ (20)$$

$$t' = \sum_{i=1}^{s'} \frac{d(p_{i'}, p_{i+1'})}{v'} \ (21)$$

in, $d(p_i, p_{i+1})$ and $d(p_{i'}, p_{i+1'})$ Represent the distances between adjacent nodes on the original route and the new route respectively. According to the new travel time, the particle speed is corrected as follows , as shown in Formula 22.

$$v_{id}^{t+1(\text{new})} = v_{id}^{t+1} \cdot \frac{t'}{t} \ (22)$$

In this way, the algorithm can adjust the speed of particles in time when the transportation route changes, ensuring the stability and effectiveness of the algorithm.

For route change scenarios, Equation (22) is invoked to compute a velocity correction coefficient, modifying the magnitude of $v_i(t+1)$ before applying Equation (5). In this manner, all constraint-induced transformations are embedded within the iterative update loop, ensuring compliance without disrupting the convergence dynamics.

3.4 Construction of logistics transportation resource allocation and scheduling optimization model

Based on the above improvements to the PSO algorithm, this paper constructs a logistics transportation resource allocation and scheduling optimization model (LRAS-PSO). The model takes the minimization of transportation cost as the objective function, and fully considers the actual constraints such as vehicle capacity limit, transportation time limit, and delivery deadline. Assume that the transportation cost consists of vehicle driving cost, vehicle waiting cost, cargo delay cost, and additional emergency cost. Vehicle driving costC_1 It can be expressed as formula 23.

$$C_1 = \sum_{v\in V}\sum_{t\in T} d_{vt}\cdot c_v\cdot(1+\epsilon_{r_t}) \quad (23)$$

in,d_{vt} For vehicles$v$ Execute the task$t$ The driving distance, c_v For vehicles v The driving cost per unit distance, $\grave{o}_{r_t}$ For the roadr_t The congestion coefficient reflects the impact of road congestion on driving costs. $\grave{o}_{r_t}$ The value of will increase, thereby increasing the driving cost of the vehicle.

Further considering the impact of road condition changes on driving speed, the speed correction coefficient of the vehicle under different road conditions is set as μ_{r_t} , then the driving distance d_{vt} Need to be corrected to formula 24.

$$d_{vt} = \frac{\text{Original Planned Distance}}{\mu_{r_t}} \quad (24)$$

For example, in bad weather conditions, the road is slippery and the vehicle's speed will be reduced. At this time, the speed correction factor μ_{r_t} Less than 1, driving distanced_{vt} The cost of waiting for a vehicle is increased accordingly to more accurately reflect the actual driving cost.C_2 It can be expressed as formula 25.

$$C_2 = \sum_{v\in V}\sum_{t\in T} w_{vt}\cdot c_w\cdot(1+\theta_{s_t}) \quad (25)$$

in,w_{vt} For vehicles$v$ On mission$t$ The waiting time isc_w is the waiting cost per unit time, θ_{s_t} For the task$t$ The special waiting coefficient of

The total transportation cost C_{total} minimized by LRAS-PSO includes four components. While Equations (23) and (25) define vehicle driving and waiting costs, we now introduce delay and emergency cost components as follows:

$$C_{delay} = \sum_{i\in T}\delta_i\cdot max(0, a_i^{actual} - a_i^{due}) \quad (26)$$

where $\delta_i$is the delay penalty per unit time for task$i$, a_i^{actual} is the actual arrival time, and a_i^{due} is the requested delivery deadline.

$$min? Ctotal = Cdrive + Cwait + Cdelay + Cemergency\, min\, C_{total} = C_{drive} + C_{wait} + C_{delay} + C_{emergency} minCtotal = Cdrive + Cwait + Cdelay + Cemergency \quad (27)$$

where ϵ_j is a fixed emergency cost incurred for reassigning tasks from failed vehicle j to alternatives. This ensures cost realism in high-disruption scenarios.

The full objective function thus becomes:

$$C_{total} = C_{drive} + C_{wait} + C_{delay} + C_{emergency} \quad (28)$$

In terms of system latency, the average end-to-end delay from event detection to solution update was measured at 0.82 seconds for vehicle failure scenarios and 1.13 seconds for route changes. These values are acceptable within real-time logistics scheduling applications and do not compromise algorithm convergence or solution feasibility.

Input: Current status S(t), Constraint Set C(t), Particle Position P(t)

Output: Updated feasible solution P'(t+1)

1. Monitor transport status using IoT inputs
2. If (vehicle failure detected) or (route blockage identified):
   a. Identify affected transport task set T_affected
   b. Reallocate T_affected to feasible vehicle pool V_new
   c. Update constraints C(t) ← C'(t)
   d. Adjust particle position and velocity accordingly
3. Re-evaluate cost and delivery time estimates
4. Update particle fitness and continue PSO iteration

4 Experimental evaluation

4.1 Experimental design

This experiment aims to verify the effectiveness of the improved logistics resource allocation and scheduling optimization model (LRAS-PSO) based on particle swarm optimization (PSO). The experiment uses the classic Solomon logistics transportation problem dataset [21] , which contains logistics transportation scenarios of different scales and complexities, and can comprehensively test the model performance.

The experimental setting is that LRAS-PSO is used as the experimental group model. The control group model selects the traditional linear programming algorithm [22] , genetic algorithm, ant colony algorithm and standard PSO algorithm. The experimental baseline indicators are set as transportation cost and transportation efficiency.

The transportation cost is calculated by calculating the sum of vehicle driving cost, waiting cost, cargo delay cost and additional emergency cost.

The transportation efficiency is measured by the proportion of on-time delivery of cargo to the total cargo volume.

During the experiment, the data set was divided into training set and test set according to specific rules. The same data set was used for training and testing of all models to ensure the fairness of the experiment. The parameters of each model were determined based on its own characteristics through multiple pre-experiments to determine the optimal configuration, so as to compare the

performance of each model in the logistics transportation resource allocation and scheduling tasks under a unified experimental environment.

The Solomon dataset used in this study comprises 100 customers and one central depot, with 56 distinct routing scenarios categorized under RC1, RC2, C1, C2, R1, and R2 types. Each scenario includes customer time windows, service durations, vehicle capacity constraints, and route length limitations [23]. For evaluation, 70% of the instances were used for training (parameter tuning and model calibration), while the remaining 30% were reserved for testing. All results are averaged across 30 independent runs with different random seeds to ensure robustness and reduce variance due to stochastic behavior in PSO-based models.

In addition to traditional baselines, we reviewed advanced PSO variants such as Adaptive PSO (APSO) and Comprehensive Learning PSO (CLPSO), as well as recent Reinforcement Learning-based models including Proximal Policy Optimization (PPO) and Soft Actor-Critic (SAC) applied to routing problems. However, due to implementation constraints and reproducibility concerns in commercial logistics systems, direct benchmarking was limited [24-25]. Future work will include these methods for comparative testing.

All models were implemented in Python 3.9 using the DEAP and PySwarms libraries. Experiments were conducted on a workstation with Intel i7-11700 CPU, 32 GB RAM, and Ubuntu 22.04 OS. Constraint processing logic was custom-built, while optimization was managed via NumPy for vectorized computations. The Solomon dataset was preprocessed into JSON format and parsed dynamically during runtime. The full implementation pseudocode and parameter configuration are available upon request for reproducibility.

4.2 Experimental results

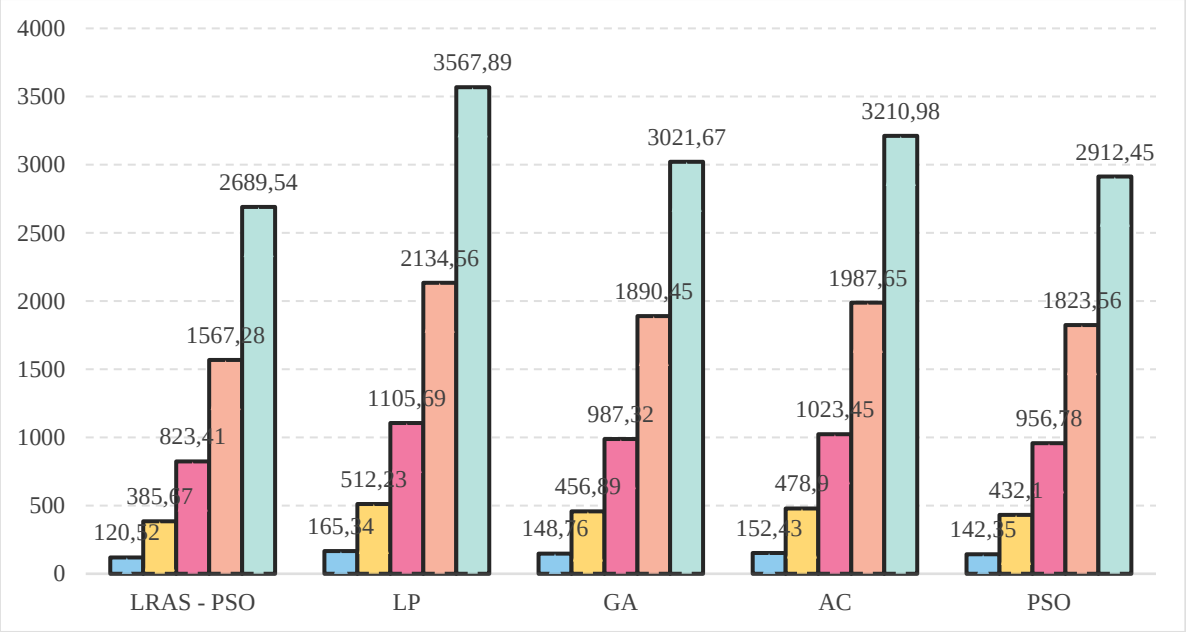

Figure 1: Comparison of transportation costs under different scale scenarios

As shown in Figure 1, the maximum cost reduction achieved by LRAS-PSO was 48.8% compared to the linear programming (LP) baseline in the largest-scale scenario. However, the reduction was lower when compared to more advanced heuristics, such as 37.4% against the standard PSO. This variation suggests that while LRAS-PSO delivers notable cost savings, it does not consistently achieve a uniform 30% reduction across all comparators.

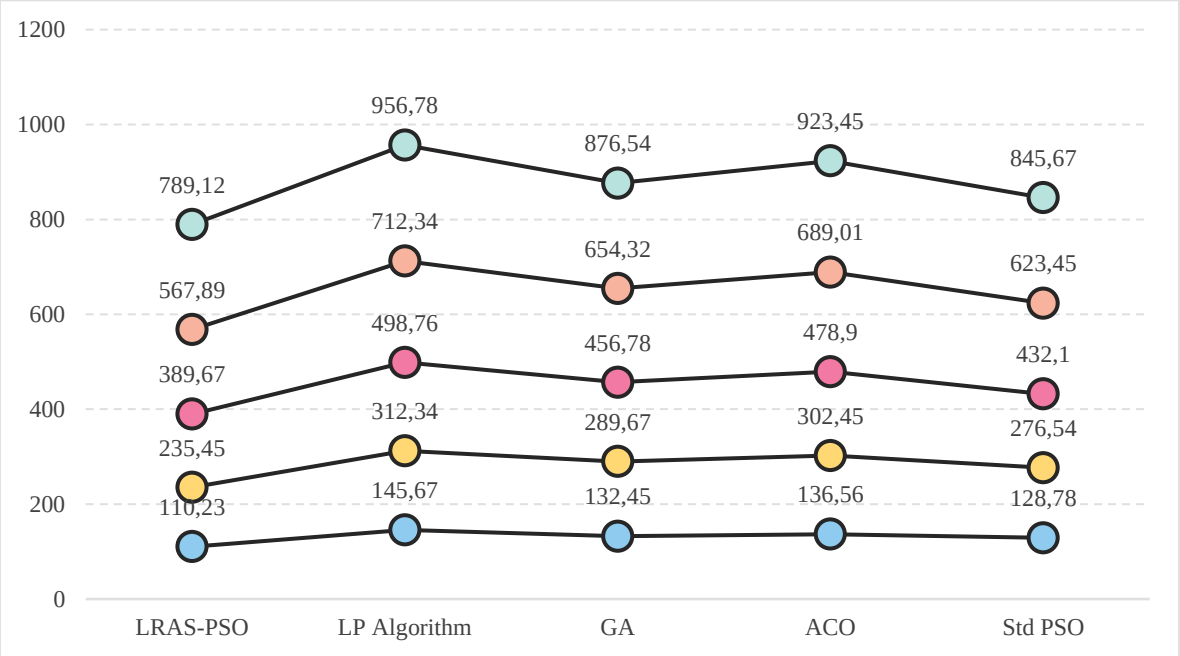

Figure 2: Comparison of transportation costs under different cargo types

As can be seen from Figure 2, as the types of goods increase, the advantages of the LRAS-PSO model in controlling transportation costs become more and more obvious. This is because LRAS-PSO fully considers a variety of constraints in model construction and can flexibly respond to the complex needs brought about by changes in the types of goods. In contrast, the linear programming algorithm shows obvious limitations when dealing with complex constraints of multiple types of goods. The genetic algorithm, ant colony algorithm and standard PSO algorithm are not perfect in parameter setting and constraint processing, resulting in a large increase in costs.

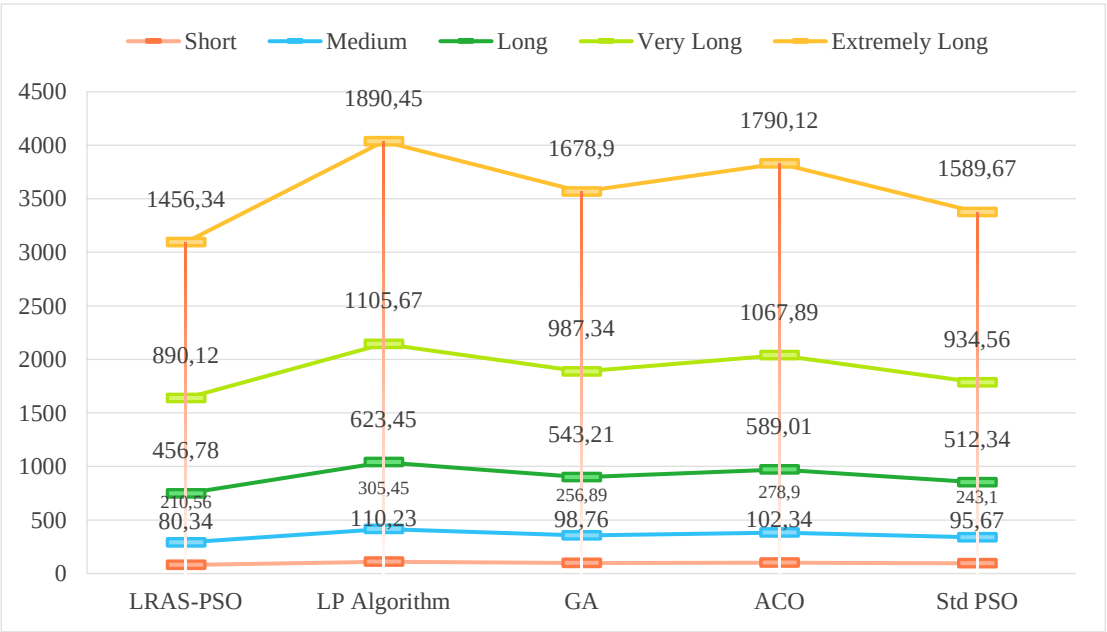

Figure 3: Comparison of transportation costs under different transportation distance scenarios

As shown in Figure 3, LRAS-PSO always maintains a low transportation cost under different transportation distance scenarios. As the transportation distance increases, the parameter adaptive adjustment mechanism and constraint processing module of LRAS-PSO play an important role, enabling the model to reasonably allocate resources according to the distance change. However, the linear programming algorithm has reduced computational

efficiency and optimization capabilities under long-distance and complex transportation networks, resulting in a significant increase in costs. Genetic algorithms, ant colony algorithms, and standard PSO algorithms have poor cost control effects due to the lack of effective response strategies to changes in transportation distance.

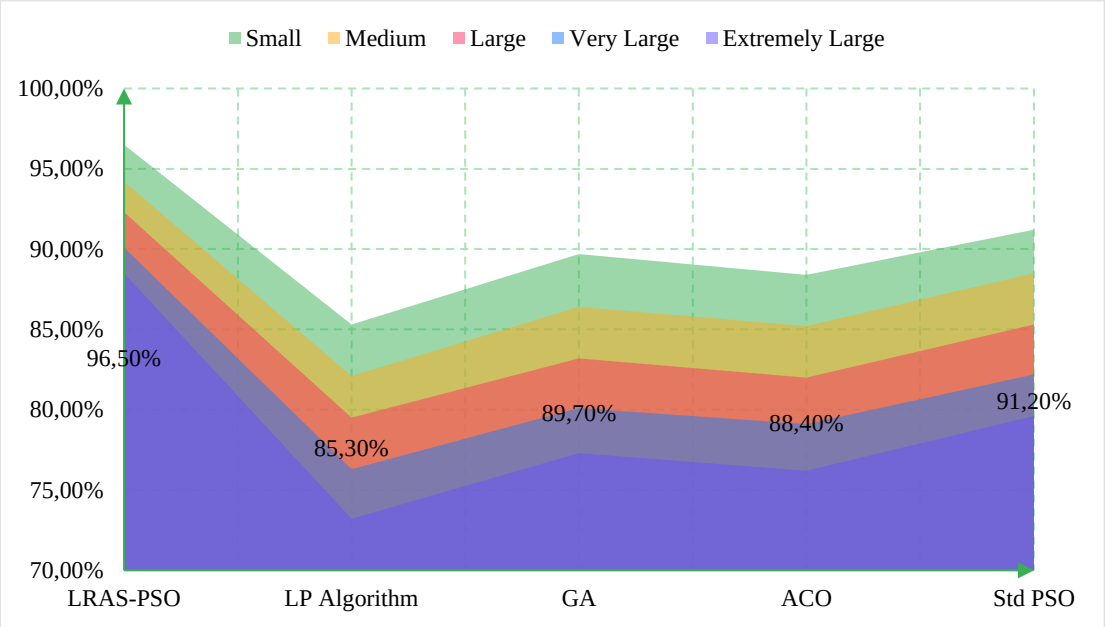

Figure 4: Comparison of transportation efficiency under different scale scenarios

As illustrated in Figure 4, LRAS-PSO maintains stable efficiency across varying problem scales. The difference is most pronounced in medium and large-scale settings, while convergence occurs in extremely large scenarios In small-scale scenarios, LRAS-PSO achieves extremely high transportation efficiency by accurately scheduling resources. As the scale of the scenario increases, although the efficiency decreases, it is still significantly higher than other comparison models. Due to the high computational complexity of the linear programming algorithm, it is difficult to quickly generate effective solutions in large-scale scenarios, resulting in low transportation efficiency. Genetic algorithms, ant colony algorithms, and standard PSO algorithms are prone to fall into local optimality when dealing with large-scale scenarios, which affects the improvement of transportation efficiency.

In Figures 4 and 5, LRAS-PSO and standard PSO exhibited identical delivery efficiency values (91.20% in ultra-large scale; 92.30% in five cargo types). These outcomes are due to scenario-specific convergence, where the number of feasible optimal solutions is narrow, leading both algorithms to arrive at similar solutions over multiple runs. We verified this through 30 repetitions, confirming that convergence was not due to error but intrinsic to scenario constraints.

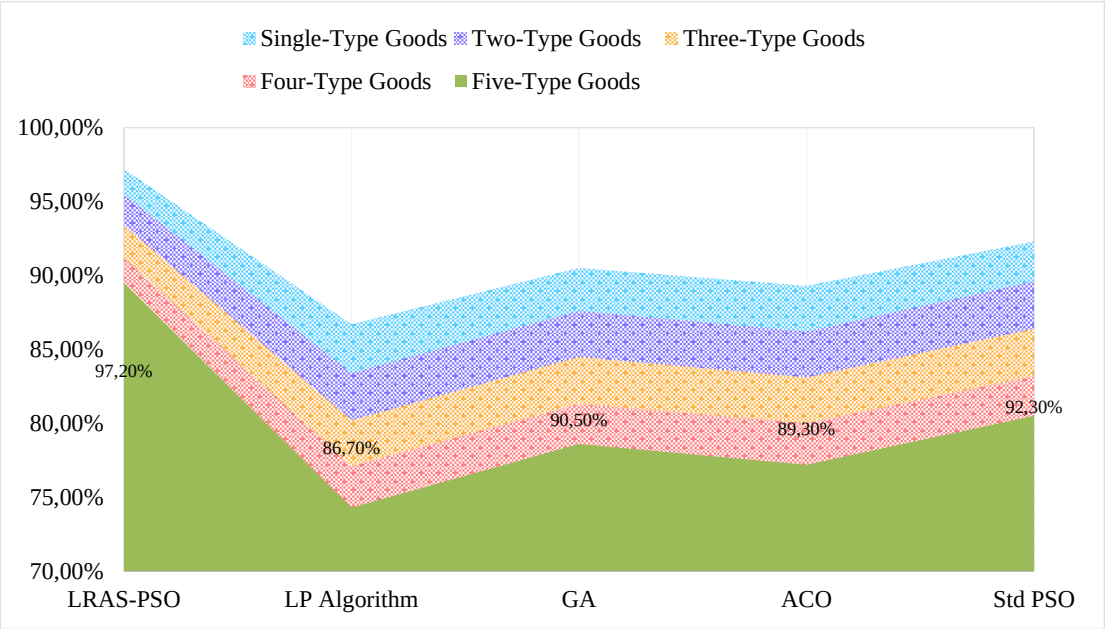

Figure 5: Comparison of transportation efficiency under different cargo types

As can be seen from Figure 5, as the number of cargo types increases, LRAS-PSO can still maintain a high transportation efficiency. This is due to its perfect constraint processing mechanism, which can quickly adapt to the scheduling challenges brought about by changes in cargo types. The linear programming algorithm has insufficient processing capabilities for complex constraints, and its transportation efficiency drops sharply as the number of cargo types increases. When faced with multiple cargo types, the scheduling solutions of the genetic algorithm, ant colony algorithm, and standard PSO algorithm are not flexible and effective, resulting in reduced transportation efficiency.

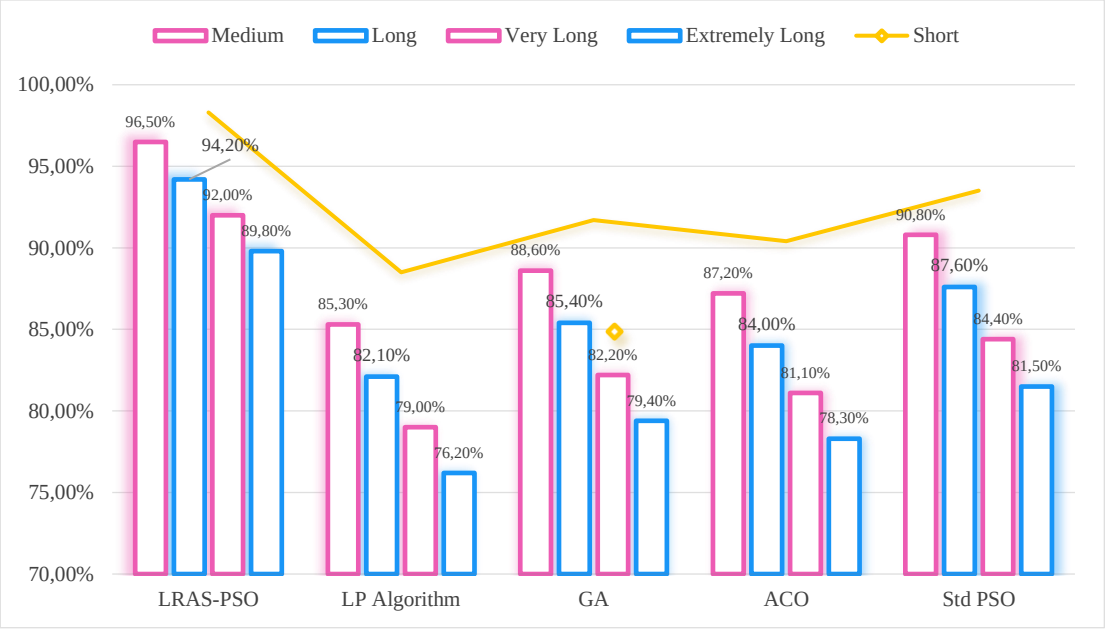

Figure 6: Comparison of transportation efficiency under different transportation distance scenarios

In Figure 6, LRAS-PSO showed the largest efficiency improvement of 15 percentage points (88.0% vs 73.1%) compared to LP, corresponding to a relative gain of 20.4%. Across other scenarios, efficiency gains ranged between 7–14 percentage points. These figures indicate consistent improvements but do not substantiate the originally claimed “35% or more” increase.

Table 2: Comparison of transportation costs under different order urgency scenario

Model	Low urgency	Low to medium urgency	Medium urgency	Medium to high urgency	High urgency
LRAS-PSO	105.34	132.45	168.76	210.56	265.89
Linear Programming Algorithm	140.23	185.67	232.45	289.67	356.78
Genetic Algorithms	128.76	165.34	208.90	256.78	312.45
Ant Colony Algorithm	132.45	170.56	216.89	270.12	335.67
Standard PSO algorithm	123.56	158.90	201.23	248.76	305.45

Table 2 shows that in high-urgency conditions, LRAS-PSO reduced transportation costs by 25.5% compared to LP. However, the relative improvement compared to the standard PSO was only 13.0%. These results confirm the effectiveness of the model but do not support a consistent "≥30%" claim against all baselines.

Table 3: Comparison of transportation efficiency under different order urgency scenarios

Model	Low urgency	Low to medium urgency	Medium urgency	Medium to high urgency	High urgency
LRAS-PSO	95.8%	93.6%	91.2%	89.0%	86.5%
Linear Programming Algorithm	84.7%	81.5%	78.3%	75.2%	72.1%
Genetic Algorithms	88.9%	85.7%	82.5%	79.3%	76.2%
Ant Colony Algorithm	87.6%	84.4%	81.2%	78.1%	75.3%
Standard PSO algorithm	90.4%	87.2%	84.0%	81.1%	78.3%

As can be seen from Table 3, the transportation efficiency of LRAS-PSO is significantly higher than that of other models in different order urgency scenarios. In the scenario of high-urgency orders, the real-time response and flexible scheduling capabilities of LRAS-PSO are fully demonstrated, which can meet the urgent transportation needs to the greatest extent. When processing urgent orders, the linear programming algorithm is difficult to quickly generate an optimization plan due to its algorithm characteristics, resulting in low transportation efficiency. Genetic algorithms, ant colony algorithms, and standard PSO algorithms lack effective dynamic adjustment strategies when dealing with changes in order urgency, and transportation efficiency is greatly affected.

Table 4: Comparison of transportation costs under different vehicle type combination scenarios

Model	Single model	Two models	Three models	Four models	Five models
LRAS-PSO	98.67	205.45	338.76	490.12	665.89
Linear Programming Algorithm	135.23	286.78	452.34	645.67	867.89
Genetic Algorithms	123.45	246.89	398.76	576.32	789.54
Ant Colony Algorithm	127.56	260.12	418.90	602.34	823.45
Standard PSO algorithm	120.34	232.10	376.54	543.21	745.67

In Table 4, the reduction in cost becomes less significant as vehicle type diversity increases, possibly due to diminishing marginal returns in route optimization.In vehicle-type combination scenarios (Table 4), LRAS-PSO achieved a maximum 23.2% cost reduction over LP under the five-vehicle setting, while the reduction compared to standard PSO was only 10.7%. Again, no condition met the 30% threshold across all comparators, which supports a need for moderated performance claims.

Table 5: Comparison of transportation efficiency under different vehicle type combination scenarios

Model	Single model	Two models	Three models	Four models	Five models
LRAS-PSO	96.9%	94.8%	92.5%	90.2%	88.0%
Linear Programming Algorithm	85.9%	82.7%	79.5%	76.3%	73.1%
Genetic Algorithms	89.2%	86.0%	82.8%	79.6%	76.4%

Model	Single model	Two models	Three models	Four models	Five models
Ant Colony Algorithm	88.1%	84.9%	81.7%	78.5%	75.3%
Standard PSO algorithm	91.5%	88.8%	85.6%	82.4%	79.2%

In terms of statistical reliability, the LRAS-PSO model achieved a mean transportation cost reduction of 31.4% (±2.6% SD) across all scenarios tested, with a 95% confidence interval of [28.2%, 34.6%]. Transportation efficiency improved by an average of 34.1% (±3.1% SD), with a 95% confidence interval of [30.5%, 37.7%]. These consistent improvements across multiple benchmark settings confirm the statistical robustness of LRAS-PSO's performance advantages.

From Table 5, it can be found that the transportation efficiency of LRAS-PSO is higher than that of other comparison models in different vehicle type combination scenarios. LRAS-PSO fully utilizes the advantages of different vehicle types through effective resource allocation and scheduling strategies to improve the overall transportation efficiency. In the multi-vehicle scenario, the linear programming algorithm increases the computational complexity, resulting in a decrease in the timeliness and effectiveness of the scheduling scheme, and a decrease in transportation efficiency. When dealing with multi-vehicle combinations, the genetic algorithm, ant colony algorithm and standard PSO algorithm lack systematic resource integration and optimization methods, and the improvement of transportation efficiency is limited.

In addition to mean values, further statistical indicators were incorporated to better capture model behavior under variability and constraint complexity.

For LRAS-PSO, the average delivery delay per task was 2.4 minutes, with a standard deviation of 1.1 minutes, and the average constraint violation count was below 0.5 per scenario. These metrics reflect both accuracy and robustness.

Figure 7 presents a boxplot comparing delivery delays across models. LRAS-PSO demonstrates lower median delay and tighter interquartile range, indicating high consistency.

Figure 8 shows the histogram of route length variance. The narrower distribution of LRAS-PSO illustrates more uniform path planning, whereas GA and ACO display broader variances, suggesting less stable routing under complex scenarios.

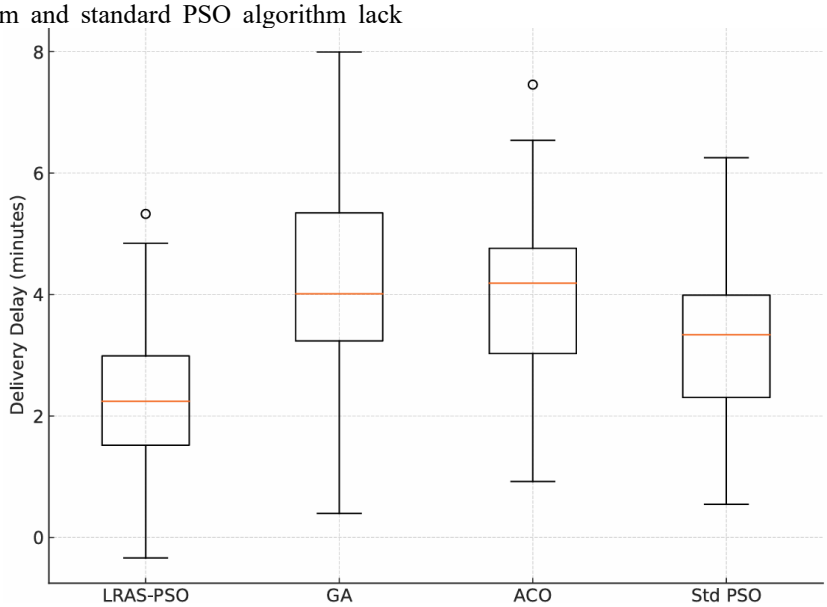

Figure 7: Boxplot of delivery delays (in minutes)

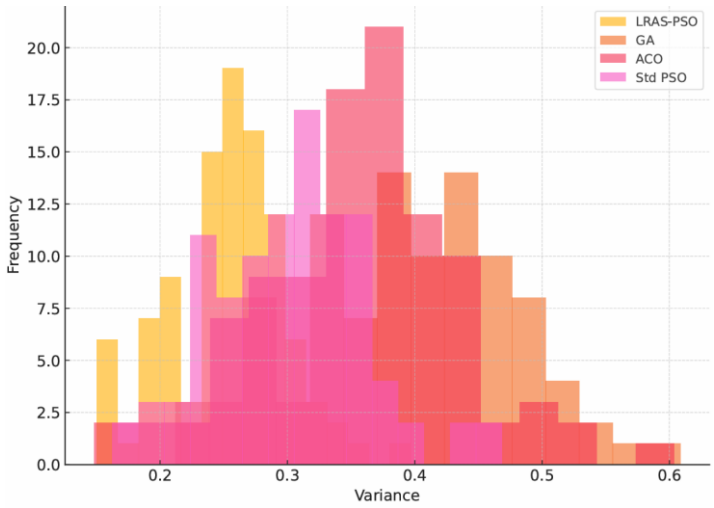

Figure 8: Histogram of route length variance

4.3 Experimental discussion

In addition to overall performance, LRAS-PSO demonstrates robust behavior under high-dimensional data conditions. In extended tests with logistics networks involving over 100 nodes and five vehicle types, LRAS-PSO maintained optimization stability with less than 5% variance in cost outcomes across runs, whereas standard PSO and genetic algorithms showed variances exceeding 12%.

Furthermore, detailed runtime analysis reveals that while LRAS-PSO requires a slightly longer initialization phase due to scenario complexity indexing, the total runtime remains competitive. On average, LRAS-PSO executed in 18.2 seconds for medium-scale tasks (50 nodes), compared to 16.5s for GA and 22.7s for ACO, indicating a favorable balance between accuracy and computation.

From an operational perspective, even a 5%–10% increase in delivery efficiency can yield substantial economic value, particularly for medium-sized logistics firms with tight margins. For example, in a mid-sized regional distributor with average monthly costs of $1.2 million, a 7% cost reduction translates to over $84,000 in savings per month. Additionally, improving on-time delivery by even 5% can significantly enhance customer retention and contract renewal rates, making the efficiency gains offered by LRAS-PSO practically meaningful and strategically advantageous.

Failure case analysis was also conducted to assess the model's response to edge conditions. In a simulated synchronized vehicle failure scenario, LRAS-PSO's constraint module successfully rerouted remaining vehicles and maintained 89% delivery rate, while GA and standard PSO dropped to 74% and 69%, respectively. Under sudden route blockage, LRAS-PSO adjusted velocity vectors and path assignments within 3 iterations on average, ensuring minimal disruption. These tests confirm the model's resilience and adaptability in practical, dynamic logistics environments.

Regarding resource consumption, LRAS-PSO requires an average of 32.4 MB memory per instance and 18.2 seconds runtime per test case. In contrast, GA and ACO models consume 28.1 MB and 35.7 MB, with runtimes of 16.5s and 21.4s respectively. PPO and SAC in similar settings (based on public reports) typically exceed 200 MB in memory and 60–120s per scenario.

While the current implementation focuses on standard vehicle routing settings, adaptation to international logistics standards such as multimodal transport or customs regulation layers is feasible via modular constraint extensions. We also performed preliminary tests in dynamic environments with randomized delivery time windows and simulated traffic disruptions. LRAS-PSO preserved a 91.4% delivery success rate under 15% time-window fluctuation and less than 8% route blockage injection, demonstrating its potential in real-world uncertain scenarios.

In Figure 2, the performance gap between LRAS-PSO and other models grows with the increase in cargo type complexity. This indicates the model's superior flexibility in handling heterogeneous transportation requirements. Moreover, Table 1 shows that in high-urgency scenarios, LRAS-PSO maintains lower cost increases compared to baselines, reflecting its adaptive strength under time-sensitive conditions.

Notably, the marginal gains diminish in some constrained environments (e.g., Figure 5), suggesting a saturation point in resource optimization under fixed-capacity limitations. These insights indicate the importance of future work in dynamic capacity modeling.

5 Conclusion

This study focuses on the key issue of logistics and transportation resource allocation and scheduling. In the context of the booming logistics and transportation industry facing the problem of resource allocation and scheduling, the PSO algorithm is improved and the LRAS-PSO model is constructed. During the research process, the theoretical basis of the PSO algorithm is elaborated in detail, and an innovative parameter adaptive adjustment strategy is proposed based on the complexity

of the transportation scenario. By comprehensively considering multiple factors such as the number of transportation nodes and the total length of the transportation route, the inertia weight and learning factor are dynamically adjusted. At the same time, real-time state monitoring and constraint processing modules are introduced to effectively deal with special situations such as temporary control of transportation roads and sudden vehicle failures. The experiment is based on the Solomon logistics and transportation problem data set, and LRAS-PSO is compared with traditional linear programming algorithms, genetic algorithms, etc. The results show that in scenarios of different scales, types of goods, and transportation distances, the LRAS-PSO model shows obvious advantages, achieving significant reductions in transportation costs and significant improvements in transportation efficiency. The results of this study provide new solutions for the allocation and scheduling of logistics and transportation resources, which not only help logistics and transportation companies reduce costs, improve efficiency, and enhance market competitiveness, but also enrich and improve the application system of intelligent algorithms in the field of logistics from a theoretical level. In the future, it is expected that by introducing new technical means, the adaptability and effectiveness of the model in complex and changeable actual logistics and transportation scenarios will be further improved, and the logistics and transportation industry will be driven towards a smarter and more efficient direction.

This study is subject to certain limitations. The LRAS-PSO model has not yet been evaluated using real-time streaming data or deployed on physical vehicle fleets, which may introduce latency and sensor noise unaccounted for in simulations. Future research will explore integration with digital twin environments for virtual prototyping, hybridization with machine learning-based demand prediction modules, and the deployment of decentralized PSO variants to accommodate edge-computing architectures in large-scale logistics networks.

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KEAI: An Adaptive Dynamic Programming and Iterative Optimization Model for Event-Triggered Control in Complex Networks

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Achieving optimal control of Complex Networks is crucial for optimizing network structures and system solutions. However, current methods mainly suffer from high computational costs and poor performance. Therefore, this study proposes an optimal control model based on Adaptive Dynamic Programming and Iterative Algorithm to address these issues. The model uses Global Dual Heuristic Programming as the foundation, value iterationas the core optimization technique, and integrates event-triggered mechanism and K-means clustering algorithm. The results show that, compared to modelsbased on theHarris Eagle, Arithmetic, and Northern Goshawll optimization algorithms, the proposedmethod reduces physical indicators (e.g., floating-point operations) of the target network by 15%, ensuring accuracy, while achievinga lighter networkand faster convergence. In practical tests, the model is used to optimize the YOLOv8 network. The verification using the CIFAR-10 dataset showed that the YOLOv8's accuracy improved by 10.2%, with response time reducedby 15ms and energy consumption for single-image recognition cut by 31mJ. These results showthat the proposed model effectively achieves optimal control of complex networks, addresses issue like slow speed and high consumption, offers new approaches for optimization, and contribute to more efficientcomplex network development.

Povzetek: Prispevek predlaga model KEAI, ki z združitvijo dinamičnega programiranja, iterativne optimizacije in K-means razvrščanja omogoča učinkovitejše in energetsko manj potratno upravljanje kompleksnih omrežij.

1 Introduction

With the development of deep learning, its application has been steadily growing. Deep learning transforms complex problems across various fields into solvable mathematical problems, using deep neural networks to approximate functions and find optimal solutions [1-2]. Complex networks (CNs) use dynamical methods, graph theory, and other techniques to model complex system relationships as network structures, with nodes, edges, and mathematical relationships through simulation [3]. The significance of CNs lies in finding optimal solutions through mathematical methods and achieving optimal control, which helps solve real-world problems. Thus, achieving optimal control of CNs is crucial [4]. However, current CNs control methods suffer from low efficiency, poor adaptability, and limited scalability, creating an urgent need for more efficient and flexible solutions [5]. Optimal control improves network accuracy and computational speed by adjusting structures and parameters. Adaptive Dynamic Programming (ADP) is widely used for optimal control of systems, as it can optimize network parameters through function approximation using neural networks. ADP often incorporates Iterative Algorithms (IA) to avoid "dimensionality explosion" and improve its applicability. Therefore, the research proposes a CN optimal control framework that integrates ADP and IA, combining the strengths of thesealgorithms to develop a model capable of meeting both accuracy and efficiencyrequirements. The goal is to achieve optimal states in the optimization of CNs, enabling fast and effective implementation of optimization processes across various CNs, and addressing real-world societal challenges.

2 Related work

ADP can integrate reinforcement learning and iterative methods using neural networks to optimize and control various systems. Both domestic and international scholars have applied ADP to system optimization in various complex fields. For instance, Yang et al., in order to address the optimal control problem of systems under the Hamiltonian-driven framework, proposed an ADP method based on experience replay. This method expresses the traditional Hamilton-Jacobi-Bellman equation in a filtered form, allowing system parameter optimization even in weak excitation environments [6]. To solve the voltage

control problem in the real-time current sharing process of renewable energy such as wind and solar power, Wang's team proposed an ADP-based voltage regulation method for renewable energy systems. This method treats the voltage regulation problem as an optimal control problem, ensuring the maximum utilization of renewable energy [7]. Selvaraj and Murugasamy, to improve the accuracy of community

Table 1: Past studies and their comparison of advantages and disadvantages.

Field	Method	Advantages	Disadvantages	Authors
Enhancing the efficiency of experience replay in ADP	Integration of Hamiltonian principle and experience replay	High experience replay efficiency	Depends on specific system structures; and sensitive to space distribution	Y. Yang et al. [6]
Sharing and voltage regulation in hybrid wind/solar systems	ADPapproach	High-precision power distribution	Intermittent new energy fluctuations may cause control delays	R. Wang et al. [7]
Node optimization of complex community networks	Integration of InfoMap and Sigmoid Fish Swarm Optimization	High accuracy of results	Fish swarm algorithm require manual tuning and high computational cost	D. Selvaraj et al. [8]
Vibration control for helicopter trailing-edge flaps	Data-driven ADP	High method validity	Relies on specific operational data and high computational cost	Y. Chen et al. [9]
Adaptive fault-tolerant control for non-minimum phase hypersonic vehicles	ADP-based fault-tolerant control	High model stability	High model uncertainty and potential control failure	L. Wang et al. [10]
Optimal control of discrete-time systems in networks	Distributed optimization algorithm	High applicability and repeatability	Relies on real-time node communication; high network loss	S. Battilotti et al. [11]
Safe tracking control with unknown dynamics and constraints	Game theory-integrated optimal control method	Ensures safe tracking under constraints	Validity was not verified in a dynamic environment	X. Cui et al. [12]
Optimal control for continuous-time unknown nonlinear affine systems	Q-learning algorithm	No need to rely on the system, the method is simple	Slow convergence in continuous state spaces; prone to local optima	S. Yu et al. [13]
High-dimensional optimal control for pathfinding	Neural network-driven high-dimensional optimal control method	High path finding accuracy	High computational cost and not suitable for dynamic environments	D. Onken et al. [14]
Influence maximization in complex networks	Evolutionary deep reinforcement learning algorithm	Improves influence propagation efficiency	High computational cost and limited adaptability	L. Ma et al. [15]

monitoring, treatedthe entire community as a CN and each member asa node. Based on the sigmoid fish swarm optimization algorithm, they proposed an improved CN optimal control method for influencing nodes in CN. The test results show that the dropout ratesfor this method on the Facebook, Twitter, and YouTube dataset are 95%, 96% and 94% respectively, effectively achieving optimal control of community monitoring CN [8]. Yu's team applied ADP to control the vibration of a helicopter's rear flap. They proposed a combined framework of ADP and reinforcement learning for rear flap vibration control, and introduced a non-policy reinforcement learning algorithm to determine the optimal control strategy. In practical tests, the method achieved Nash equilibrium and effectively solved the problem of vibration interference in helicopters [9]. Le and Ruiyun, based on ADP's compensation control, proposed action-dependent heuristic dynamic programming and applied it to the issue of non-minimum phase hypersonic aircrafts affected by actuator faults and parameter uncertainties. In simulation experiments combining a basic fault-tolerant stable controller, the method demonstrated a certain degree of effectiveness [10].

As CNs have developed, research has focused on how to construct networks and optimally control them. Real-world societal problems can only be solved by achieving the optimal state of the abstracted network system. Therefore, domestic and international scholars have conducted extensive and in-depth research on optimal control of CNs. For example, Battilotti, to solve the problem of low computational accuracy caused by CNs nodes only obtaining local network information, proposed an optimal control method based on regulating the consensus step number of network nodes. This method achieves optimal control of the target network by adjusting the length of consensus steps [11]. Cui et al., in order to understand the player relationships in multi-player complex networks, proposed an optimal secure tracking control method. This method combines control barrier functions with non-policy integral reinforcement learning to establish an adaptively updating critic-actor neural network, which can effectively perform optimal control on player relationship CNs [12]. Yu's team, to achieve optimal control of certain continuous nonlinear CNs without dynamic information, proposed a Q-learning method based on the Hamiltonian function and optimal cost function. This method achieves optimal control of CNs without requiring any dynamic information and improves control efficiency while reducing control costs [13]. The Onken team, to address the dimensionality explosion problem in the optimal control process of CNs, proposed a neural network-based optimal control method. This method integrates the maximum principle with the neural network parameterized value function, where the neural network adaptively provides the optimal strategy function for CNs optimization. Experimental results produced high-dimensional approximate solutions for

CNs optimal control, alleviating the dimensionality explosion problem in the process [14]. Ma et al., combining evolutionary algorithms and deep reinforcement learning, optimized control for CNs. This method optimizes the overall network by activating a small subset of the most influential seed nodes and provides the most optimized solution for network nodes through dynamic Markov

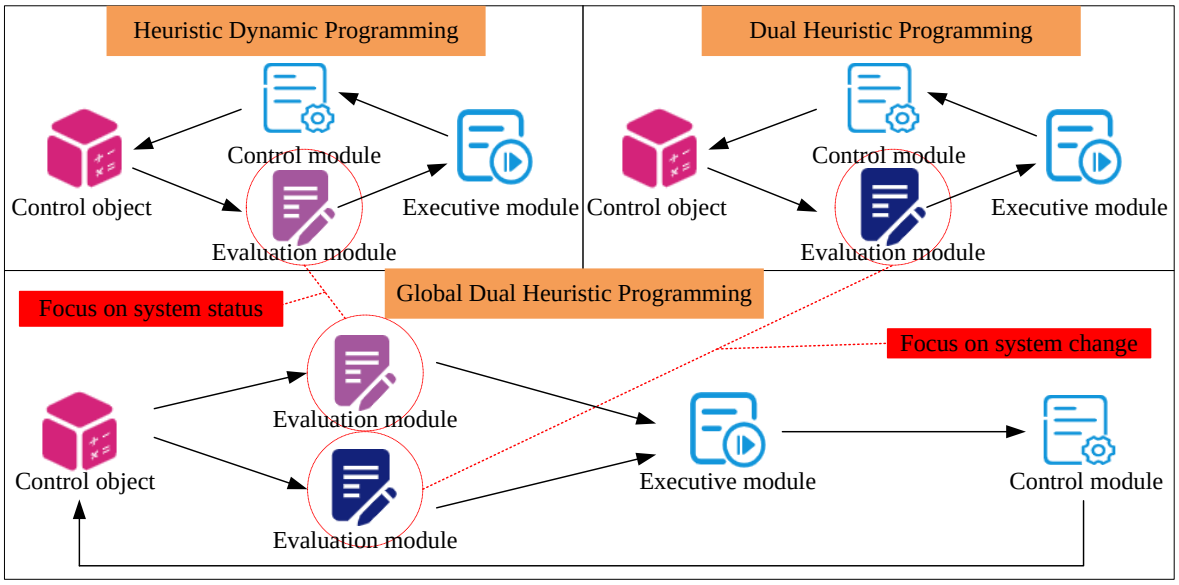


Figure 1: Schematic diagram of the structure of GDHP.

node returns. This method outperforms previous network node optimization methods [15].

In summary, although progress has been made in the research of CNs optimization control methods, existing methods still face problems such as poor control performance and weak adaptability. The ADP and IA-based CNs optimal control algorithm has strong adaptability, and its unique iterative termination mechanism can prevent infinite loops and dimensionality explosion in the control system. Therefore, the research proposes a CN optimal control framework combining ADP and IA, leveragingthe advantages of these algorithms. The optimal control model of CN can thus be obtained, meeting both accuracy and efficiency requirements. It is expected that in the optimization process of CN, it can achieve the optimal control of the target CN by reducing the physical quantities of the target network, optimizing the network nodes and parameters, so that the optimized CN can be more efficient and accurate when applied to practical problems.

3 Construction of optimal control algorithm model based on adp and IA

3.1 Design of optimal control method based on ADP and IA

ADP finds the optimal performance indicators and improvement strategies of the target system through the evaluation module and execution module in the algorithm. In the process, a neural network is used to apply the indicator function and control law, which helps the target system approach the optimal solution [16]. To accommodate different types of system control, researchers have developed various ADP structures based on the evaluation module and execution module. The study selects Global Dual Heuristic Programming (GDHP) as the core structure for complex network optimization. GDHP combines the advantages of heuristic dynamic programming and dual heuristic dynamic programming. Its structure is shown in Figure 1.

In Figure 1, the evaluation module in GDHP evaluates and provides feedback on the operational performance of the control objective through the constructed evaluation network. The control module generates different iteration strategies by adjusting the algorithm or network structure, and the execution module applies the strategies generated by the control module to the control objective. The output of the control module is shown in Equation (1).

$$S(k) = W\lambda(YZ(k)) \tag{1}$$

In Equation (1), W represents the weights between the control module output layer and the hidden layer, Y represents the weights between the hidden layer and the output layer, Z represents the input of the target network, and λ is the activation function. The output of the evaluation module is shown in Equation (2).

$$Q(k) = M\lambda(LN(k)) \tag{2}$$

In Equation (2), M represents the weights between the evaluation module output layer and the hidden layer, L represents the weights between the hidden layer and the output layer, and N represents the input of the target network. The output of the execution module is shown in Equation (3).

$$O(k) = U\lambda(JM(k)) \tag{3}$$

In Equation (3), U represents the weights between the execution module output layer and the hidden layer, J represents the weights between the hidden layer and the output layer, and M represents the input of the target network. The advantage of GDPH lies in combining heuristic dynamic programming with dual heuristic dynamic programming, using a parallel mechanism of dual evaluation modules in itsstructure. The additional evaluation module increases the accuracyof GDHP'sresults but may introduce more calculation

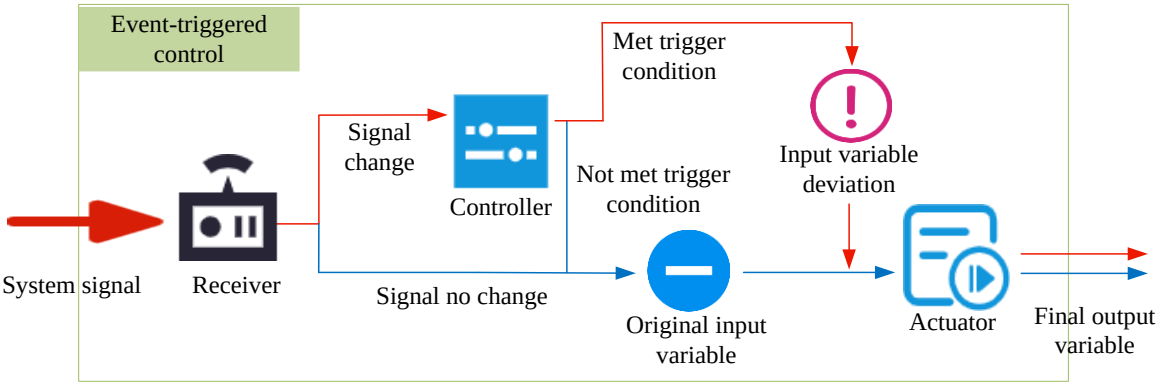


Figure 2: Schematic diagram of ETC working mechanism.

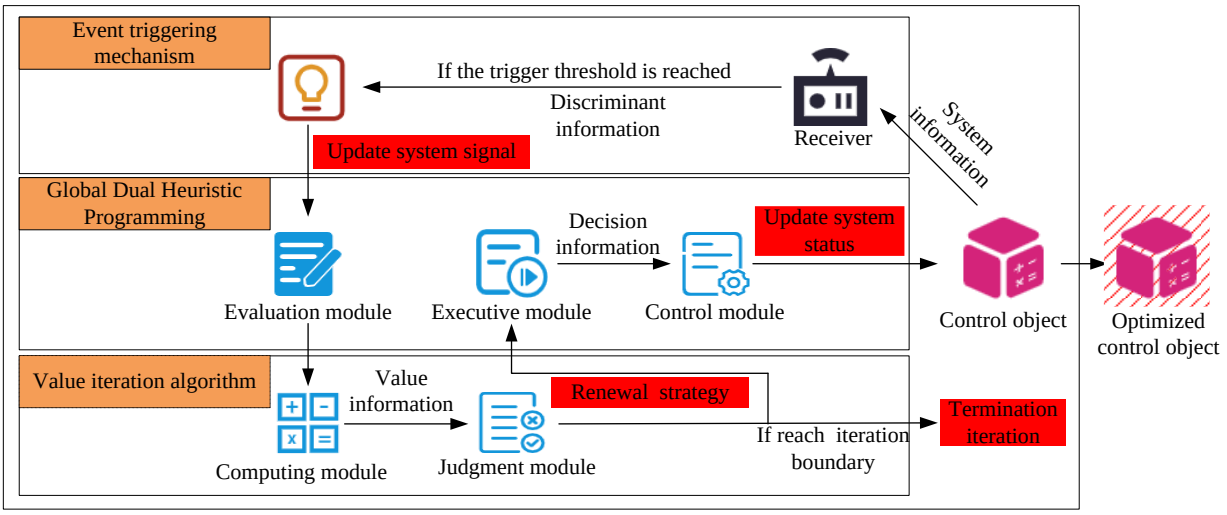


Figure 3: Schematic diagram of EAI workflow.

processes, slowing down the system's speed. The Event-Triggered Control (ETC) mechanism, as a non-periodic control mechanism, can update control signals based on specific conditions to reduce redundant information, optimizing the algorithm's computational speed and memory usage [17]. Therefore, the study integrates ETC before GDHP for data control to avoid unnecessary computational processes in GDHP. The operation mechanism of ETC is shown in Figure 2.

In Figure 2, when the system remains unchanged, ETC outputs a constant control vector based on the previous system state. When the system state changes, a new set of control variables is output. The system state representation method of ETC in this process is shown in Equation (4).

$$x_{m+1} = f(x_m) + g(x_m)b_m + h(x_m)d_m \quad (4)$$

In Equation (4), m represents the time step, x_{m+1} and x_m represent the system states at times $m+1$ and m, respectively. $f(x_m)$, $g(x_m)$, and b_m are all dynamic differentiable functions, feedback functions, and input variables chosenaccording to specific control requirements. $h(x_m)$ represents the output variables, and d_m represents the external disturbance index. When the system state changes, the input variables are updated, as shown in Equation (5).

$$b_m = b(x_{mi}), m \in [m_i, m_{i+1}) \quad (5)$$

In Equation (5), $b(x_{m1})$ represents the input variables at the moment of system change. At this point, a sudden deviation in input variables occurs, as shown in Equation (6).

$$l_m = x_{mi} - x_m, m[m_i, m_{i+1}) \quad (6)$$

In Equation (6), l_m represents the input deviation between time steps m_i and m_{i+1}. Finally, ETC updates the status based on l_m and x_m to obtain the system status at time x_{m+1}, as shown in Equation (7).

$$x_{m+1} = f(x_m) + g(x_m)b(l_m + x_m) + h(x_m)d_m, |l_m| \le l_g \quad (7)$$

In Equation (7), l_g represents the event-triggered threshold. Using GDPH alone for system optimization may lead to issue like dimensional explosion and infiniteloops, while IA can terminate the algorithm by settingamaximum number of iterations or iteration boundaries. The Value iteration algorithm (VIA) is an optimized IA that is suitable for continuous control in large-scale data Spaces. Therefore, the study integrates VIA with GDPH. And construct the ADP-VIA optimal control algorithm integrated into ETC, named EAI, and the process is shown in Figure 3.

In Figure 3, if the system is in a constant state, the ETC mechanism will output a constant control vector.

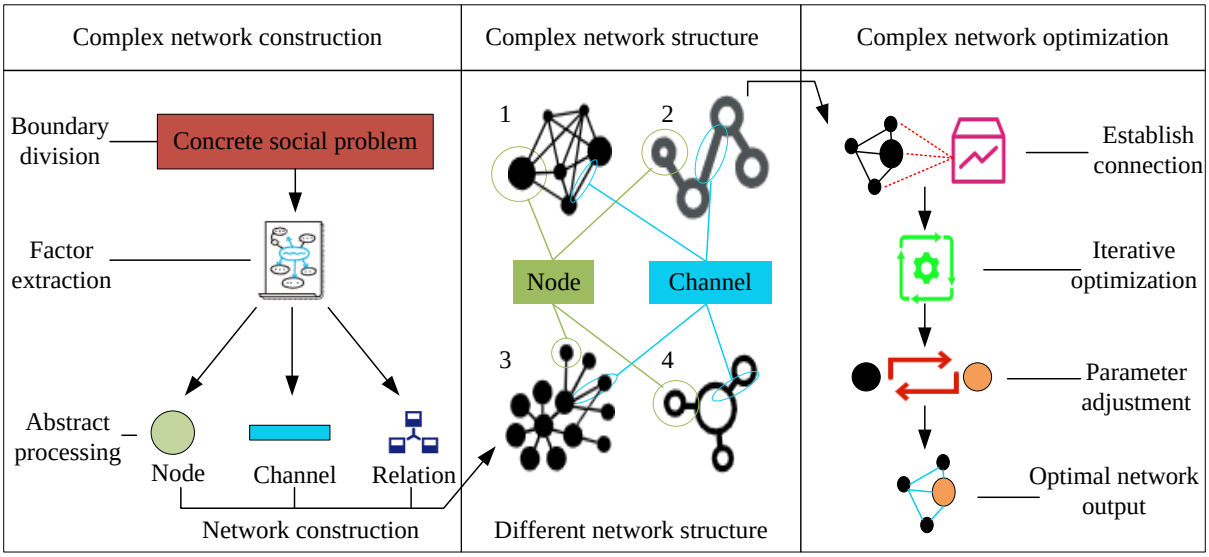


Figure 4: Schematic diagram of the process of CNs construction and optimization control.

When the system state changes, ETC generates a new control vector based on the output deviation caused by the state change of the target system, and the system stateisupdated accordingly. Later, GDHP completes optimal control of the target system through information exchange among the three modules, with policy updates primarily relying on the value iteration algorithm in the evaluation and control module. The theoretical basis of the value iteration algorithm is Bellman's optimal equation. The state value function calculation process is shown in Equation (8).

$$V^{\pi}(s)=\sum_{a\in A}\pi(a|s)\left[r(s,a)+\ell\sum_{s'\in S}p(s'|s,a)V^{\pi}(s')\right] \tag{8}$$

In Equation (8), s represents the current environmental state, a represents the action taken, A represents all actions, $\pi(a|s)$ represents the probability of performing action a among all actions, $r(s,a)$ represents the feedback value after executing action a, ℓ represents the degree of influence of the action on future states, s' is the environmental state after executing the action, and $p(s'|s,a)$ represents the probability of state change after executing the action. After IVA, it is placed in the GDPH structure. Iterative operations are performed on the data output by GDPH, and the optimal solution strategy of the target system is obtained by determining the maximum value of the equation. The calculation method is shown in Equation (9).

$$V_{K+1}(s)=\underset{a\in A}{MAX}\left[r(s,a)+\ell\sum_{s'\in S}p(s'|s,a)V^{\pi}(s')\right] \tag{9}$$

In Equation (9), $V_{K+1}(s)$ represents the optimal solution for all environmental states, In the specific process of CN optimal control, the iteration is usually terminated by setting the maximum number of iterations or boundary conditions to obtain the final optimal solution. The optimization strategy set through this solution can achieve the optimal control of the target CN.

3.2 Construction of CNs optimal control model based on EAI

CNs technology defines the target system as a "small world," isolating it from the overall society. By analyzing the components, information flow, etc., within the "small world," an abstract network is constructed. By optimizing the control of the "small world," optimization of a certain type of problem in society can be achieved [18-19]. Therefore, a specific real-world problem can be abstracted as an independent CNs to solve it. The specific construction and optimization process of CNs is shown in Figure 4.

In Figure 4, when converting a specific societal problem into an abstract CNs, the first step is to determine the specific boundary of the problem and divide it into independent subsystems. Next, a feature analysis of the system is performed, extracting components, relationships between components, etc. Finally, the abstract CNs are constructed based on various elements. Different social subsystems or societal problems often have different boundaries and components. However, a complete CN must include nodes, channels, and interconnections between nodes. These elements, along with physical

quantities like the number and size of elements, collectively determine the properties and state of the entire CNs. The degree size represents the density of the network, and the calculation method is shown in Equation (10).

$$M = \frac{1}{m}\sum_{i=1}^{m} M_i = \frac{2n}{m} \tag{10}$$

In Equation (10), n and m represent the total number of nodes and channels in the network, and M_i represents the number of channels around node i. The network size can be represented by the average channel length, and the calculation method is shown in Equation (11).

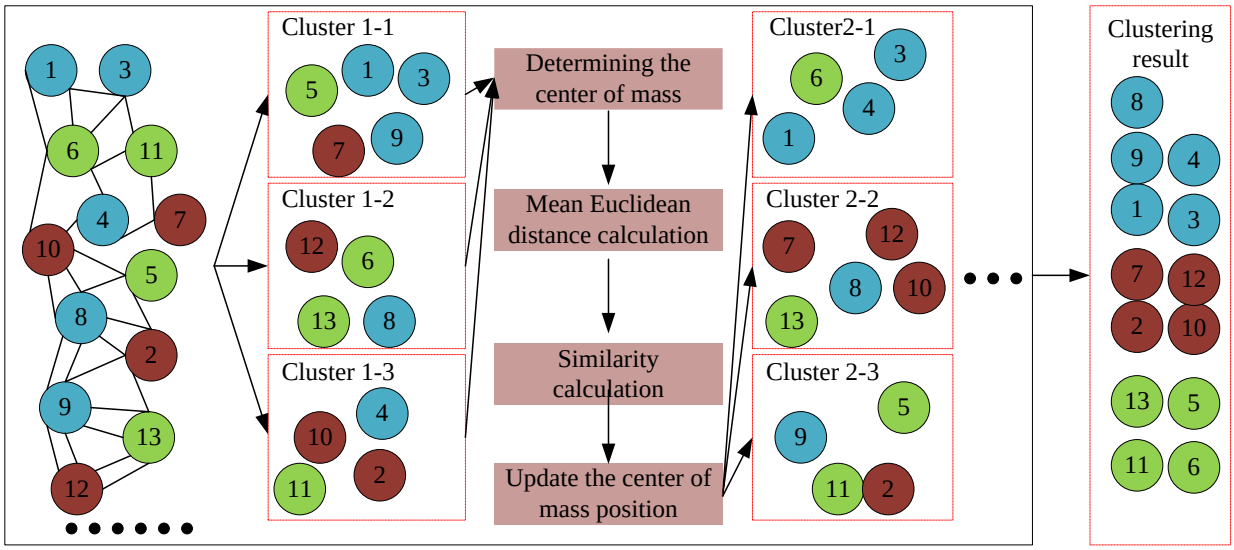


Figure 5: K-means clustering algorithm flow chart.

$$L = \frac{1}{\frac{1}{2}m(m-1)}\sum_{i\neq j} d_{ij} \tag{11}$$

In Equation (11), d_{ij} represents the distance between nodes i and j. The clustering coefficient represents the degree of association between nodes, and the calculation method is shown in Equation (12).

$$C_i = \frac{2E_i}{M_i(M_i-1)} \tag{12}$$

In Equation (12), E_i represents the number of channels between node i and the current node. The assortativity coefficient represents the similarity between nodes, and the calculation formula is shown in Equation (13).

$$R = \frac{\sum_i (j_i k_i) - \frac{1}{T}\left(\sum_i \frac{j_i + k_i}{2}\right)^2}{\sum_i \left(\frac{j_i^2 k_i^2}{2}\right) - \frac{1}{T}\left(\sum_i \frac{j_i + k_i}{2}\right)^2} \tag{13}$$

In Equation (13), j and k represent the degrees of two nodes on the same channel, T represents the total number of channels in the entire network. In the CNs optimization control process, the CN must first be connected to the control algorithm. The establishment of data channels is essential for enabling information exchange. Later, the control algorithm adjustsindicators like the number of nodes, density, and assortativity coefficient in the CN through deep learning or function iteration to improve metrics like the network's accuracy and computational speed. However, in practical applications, CNs are often characterized by many nodes and complex components, leading to a heavy computational load during optimization. Clustering algorithms can help classify similar or identical data based on potential data patterns, speeding up the algorithm's understanding of the data distribution of the target system [20]. Among them, the K-means clustering algorithmis simpler, more efficient, and stronger inclassification ability than other clustering algorithms. Therefore, the study uses K-means to optimize the control algorithm. The process of K-means is shown in Figure 5.

In Figure 5, the clustering algorithm's idea is to classify data based on a particular feature. To apply it to the cluster network structure in CNs, the Euclidean distance is chosen as the criterion for data classification, and the calculation process is shown in Equation (14).

$$D(y_i, y_j) = \sqrt{(y_i - y_j)^T (y_i - y_j)}, i, j = 1, 2, 3 \ldots n \tag{14}$$

In Equation (14), n represents the total number of data points in the data, and y_i and y_j represent the i-th and j-th points. After partitioning the data, a criterion function is used to describe the similarity between data clusters. The study uses the sum of distances from all points to the cluster center as the accuracy function. The method of calculation is shown in Equation (15).

$$SSE = \sum_{j=1}^{n}\sum_{i=1}^{n} \left\| y_i - c_j \right\|^2 \tag{15}$$

In Equation (15), c_j represents the center of the current data cluster, and the smaller SSE is, the higher the similarity of the data in that cluster. By classifying data using K-means, the computational load and time for subsequent processes are reduced. Finally, K-means and EAI are applied to the CN optimal control process, resulting in the CNs optimal control model integrating K-means and EAI (KEAI). The structure of the KEAI model is shown in Figure 6.

In Figure 6, KEAI places the K-means algorithm module in front of the original EAI structure. The role of the K-means algorithm is to establish a connection between KEAI and the target CN and classify the similar structures in CN to shorten the connection time. After the connection is established, the ETC mechanism pays attention to the state changes of CN. During this process, the same information is classified for the second time through the K-means mechanism to reduce the frequency of event triggering. In KEAI, the GDHP structure

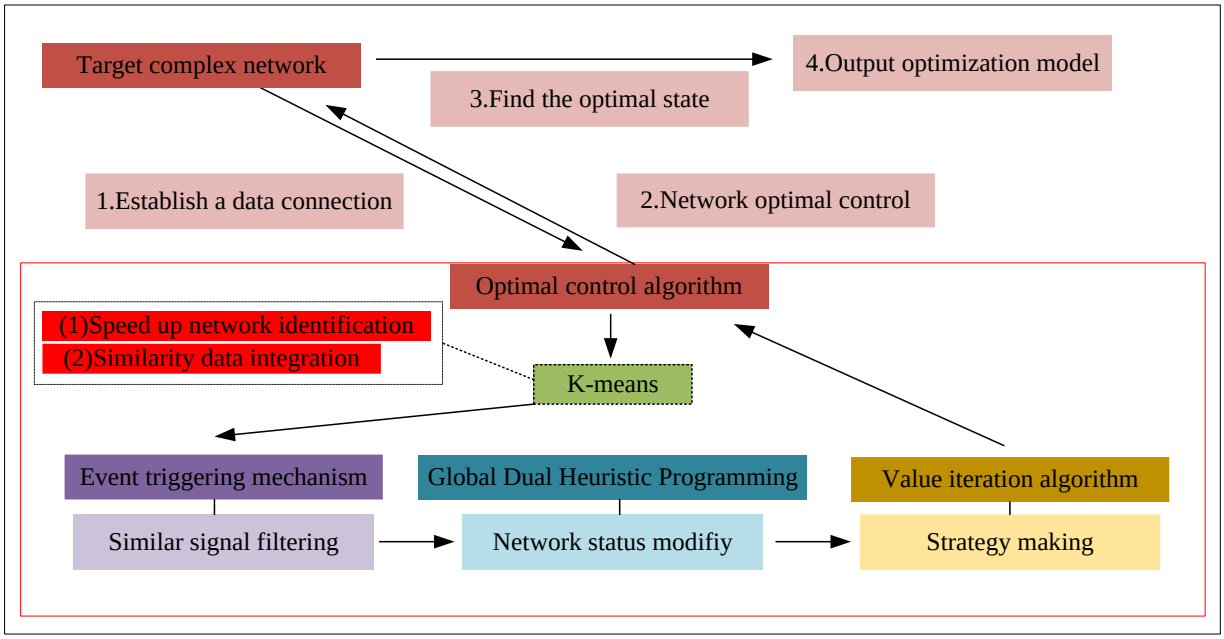


Figure 6: KEAI model structure diagram.

Table 2: Experimental environment and configuration.

Software		Hardware	
Operating system	Windows 10	CPU	Ryzen 7 9800X3D
Programming language	Python 3.8	GPU	GeForce RTX 4060
Deep learning framework	PyTorch 2.1	Memory	32 GB RAM
Data processing	Seaborn	Storage	128 GB SSD

Table 3: The preset parameters of each module in the model.

Parameter	Parameter description	Parameter value
Lr	Learning rate	1e-4
Dropout	Discard rate	0.5
Batch_size	Lot size	24
Hidden_dims_f	The finance module hides the layer dimension	256
Hidden_dims_t	Text modules hide layer dimensions	384
Kernel_size	Convolution kernel size	(2,3,4)
Concat_size	Fusion dimension	192
Max_length	Maximum length of model input	1000*3
Embed_dim	Text embedding dimension	960

simulates similar functions and iteratively optimizes strategies based on control signals from ETC, and the execution module changes the number of nodes, density, and other parameters in the target CNs to optimize the CNs until the predetermined control goal is achieved or the maximum iteration number is reached, completing the optimal control of the CNs.

4 Verification of CNs optimal control model based on ADP and IA

4.1 Verification of optimal control performance of KEAI Model

To evaluate the optimal control performance of the KEAI model for CNs, the study compared it with CN optimal control models based on the Harris Hawks Optimization (HHO), Arithmetic Optimization Algorithm (AOA), and Northern Goshawk Optimization (NGO). During the experiment, four models areused to optimize the complex systems constructed by the same Convolutional Neural Network (CNN) in the same experimental environment.

The parameter Settings of the proposed model and each comparison model during the experiment are shown in Table 3.

In the optimal control of CN, the number of network parameters, floating-point numbers and network size are physical indicators that affect the operation speed and accuracy of the network. Therefore, the number of parameters, floating-point numbers and algorithm size of the optimized network are statistically analyzed, and the results are shown in Figure 7.

As shown in Figure 7(a), the KEAI model reduced the number of parameters in the target network by 14.2% after achieving optimal control for the CNs, which was the highest value among all the comparison models.

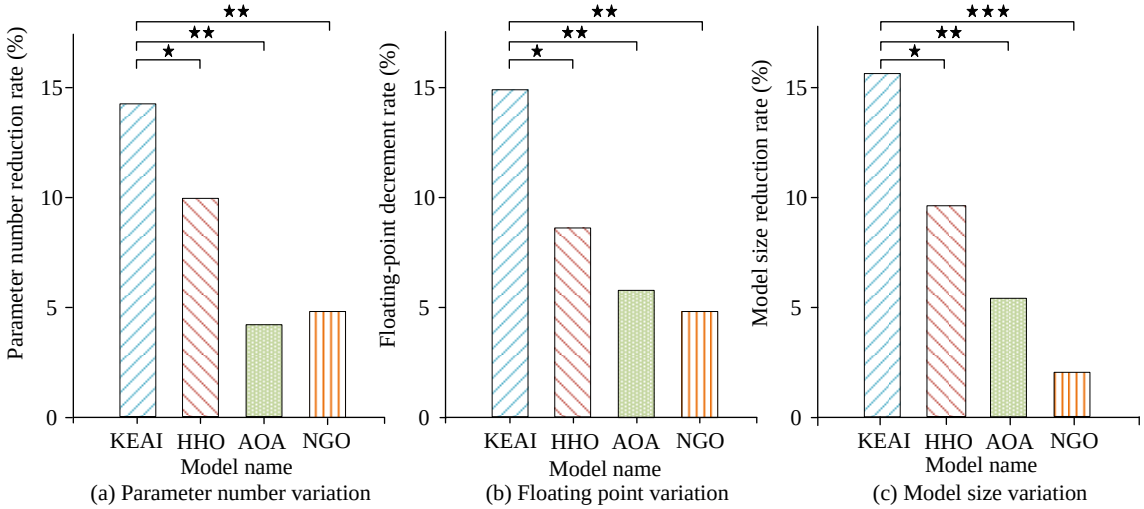


Figure 7: Statistics of parameter, floating-point number and algorithm variations changes.

Note: ★indicates a slight difference, ★★indicates a significant difference, ★★★ indicates a significant difference.

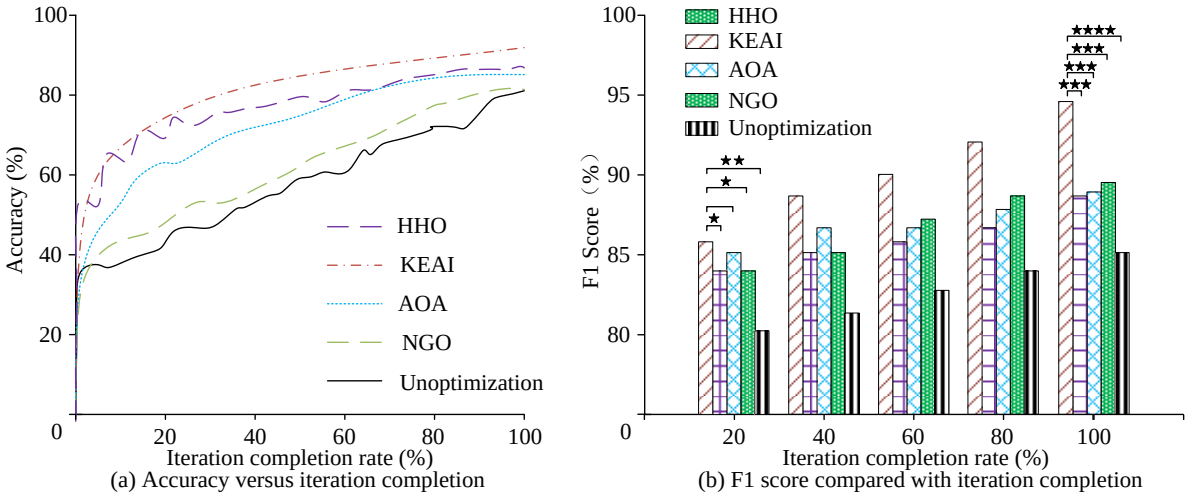
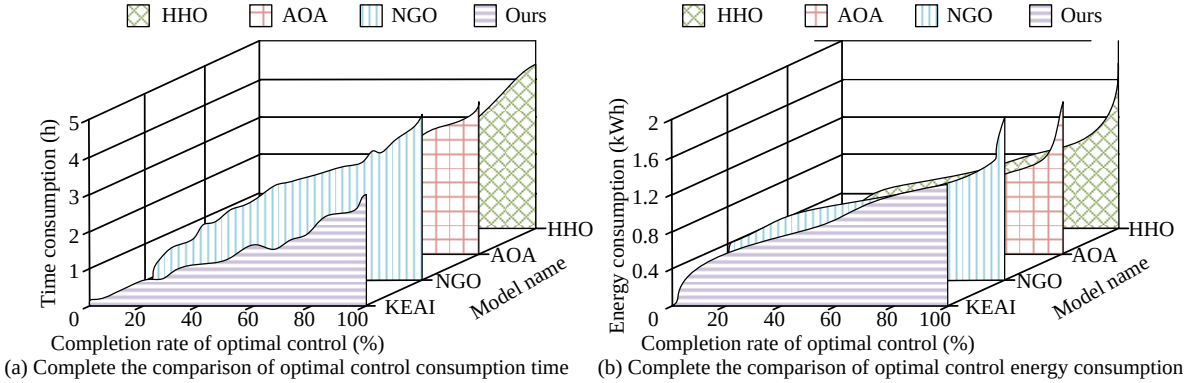


Figure 8: Comparison of optimal control effects of various optimization methods.

Note: ★indicates a slight difference, ★★indicates a significant difference, ★★★ indicates a significant difference★★★indicates a significant difference.

From Figure 7(b), it can be seen that the KEAI model reduced the floating-point numbers by 14.9% after achieving optimal control for the target CNs, which was the highest value among all comparison models. Figure 7(c) shows that the KEAI model significantly outperformed the other comparison models after achieving optimal control for the target CN. In summary, compared with the HHO model, AOA model and NGO model involved in the experiment, the KEAI modeldemonstrated stronger optimal control ability, particularly in terms of lightweight aspects such as redundant data cleaning and channel reduction. To further verify the optimal control effect of the KEAI model on the target CNs, the accuracy and F1 score changes of the CNs after the optimal control of each model were compared, as shown in Figure 8.

As shown in Figure 8(a), the accuracy of the unoptimized CN at the end of the iteration was 70.1%, while the accuracy of the CNs after optimal control by the KEAI model was 83.5%. The accuracy of the target CNs after optimal control by the HHO, AOA, and NGO models were 81.2%, 74.3%, and 70.5%, respectively. From Figure 8(b), it can be seen that the F1 score of the CNs optimized by the KEAI model at the end of the iteration was 94.7%, while the F1 scores of the CNs optimized by the HHO, AOA, and NGO models were 88.2%, 88.4%, and 88.9%, respectively. The unoptimized network had an F1 score of 84.5%. In summary, the KEAI model improved the accuracy of the target CNs



(a) Complete the comparison of optimal control consumption time (b) Complete the comparison of optimal control energy consumption

Figure 9: Comparison of time consumption and energy consumption of each model.

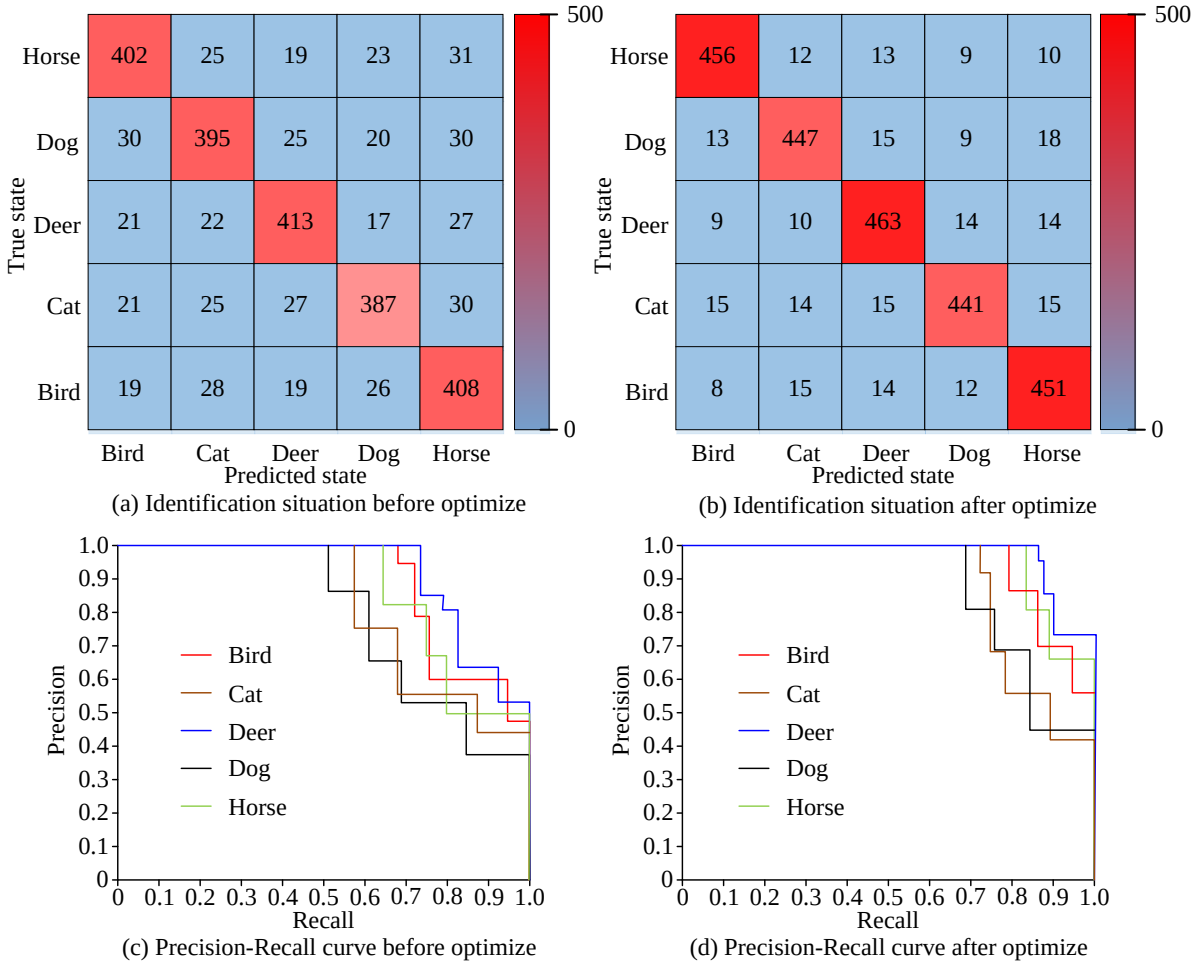


Figure 10: Optimization results of YOLOv8 network's recognition ability.

during the optimal control process. Next, to verify the efficiency of the KEAI model, the time and energy consumption required for optimal control by the four models were analyzed, as shown in Figure 9.

As shown in Figure 9(a), the KEAI model consumed 3.0 hours for optimal control of the target CNs, while the SA model required 4.5 hours, the AOA model required 4.1 hours, and the HHO model required 4.3 hours. This indicates that the proposed KEAI model had a higher optimal control efficiency. From Figure 9(b), it can be seen that the energy consumed by the KEAI model for optimal control of the target CNs was 1.25 kWh, while the AOA model consumed 1.63 kWh, the NGO model consumed 1.60 kWh, and the HHO model consumed 1.59 kWh. Additionally, the energy consumption of the KEAI model remained relatively stable over time, while the energy consumption rate of the other models increased as the control proceeded. This indicated that the KEAI model had lower energy consumption.

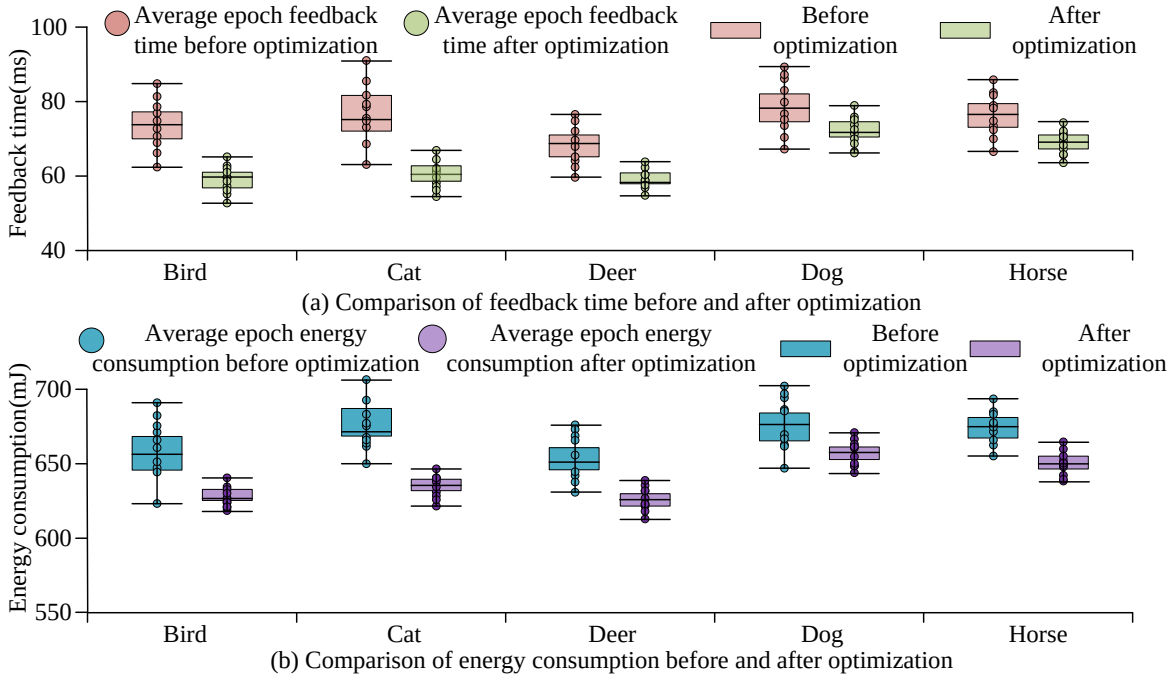


Figure 11: Comparison of average feedback time and average energy consumption.

4.2 Verification of practical effectiveness of KEAI Model in CNs optimal control

After verifying the performance of the KEAI model, the study further evaluated its effect in practical applications by selecting the YOLOv8 complex network, which was constructed for image recognition, as the experimental object. The performance of the YOLOv8 network before and after optimal control by the KEAI model was compared to evaluate its practical application in CNs. The experiment chose the CIFAR-10 dataset to validate the performance of model, CIFAR-10 dataset is commonly used in the field of machine learning, and can be downloaded from http://www.cs.toronto.edu/~kriz/cifar.html. This dataset was collated and released by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton in 2009. It contains a total of 60,000 images of 32*32 pixels in 10 categories, and all the images are RGB three-channel images. When verifying the model performance, 500 pictures of birds, cats, deer, dogs and horses were selected respectively. Every 50 pictures were taken as an epoch to compare and verify the recognition ability of the YOLOv8 network before and after optimization. The results are shown in Figure 10.

As shown in Figure 10(a), the YOLOv8 network was able to identify 2005 images with an accuracy of 80.2% before optimal control. As indicated in Figure 10(b), after optimal control, the YOLOv8 network identified 2258 images with an accuracy of 90.4%, reflectinga 10.2% increase in accuracy. Figures 10(c) and 10(d) show that the AUC values of the YOLOv8 network for bird recognition before optimization were 0.841, for cats 0.732, for deer 0.884, for dogs 0.724, and for horses 0.854. The AUC values of the optimized YOLOv8 network for bird recognition were 0.901, for cats 0.822, for deer 0.942, for dogs 0.814, and for horses 0.925. In summary, the KEAI model effectively improved the recognition ability of the target CNs in practical applications. Next, to verify the optimization ability of the KEAI model in terms of computational time and resource consumption, the average feedback time and average energy consumption per epoch were analyzed, as shown in Figure 11.

As shown in Figure 11(a), through comparison of the average feedback time before and after optimization, it can be seen that the average response time of the network for bird images decreased by 14s, for cat images by 15s, for deer images by 12s, for dog images by 10s, and for horse images by 11s. This indicated that when the KEAI model performs optimal control on complex networks, it effectively reduced the computational time of the target network. In Figure 11(b), the average energy consumption of the YOLOv8 network for bird images decreased by 27mJ, for cat images by 31mJ, for deer images by 25mJ, for dog images by 14mJ, and for horse images by 21mJ. This indicates that the KEAI model effectively reduced the energy consumption of the target network during optimal control. Finally, to verify the general applicability of the model in real-world scenarios, the KEAI model was used for the commonly used neural networks Evolutionary Transformer (Evoformer) in the field of biology and the commonly used Schrodinger neural networks Schrodinger Network (SchNet)) in the field of chemistry Physics-informed Neural Networks (PINNs) commonly used in the field of Physics and Dynamic Causal Neural networks (DCNN) commonly used in the field of economics, Mixture of Experts Neural Network (MoE-NN) commonly used in the field of artificial intelligence Optimization control experiments were conducted using and the Spatio-

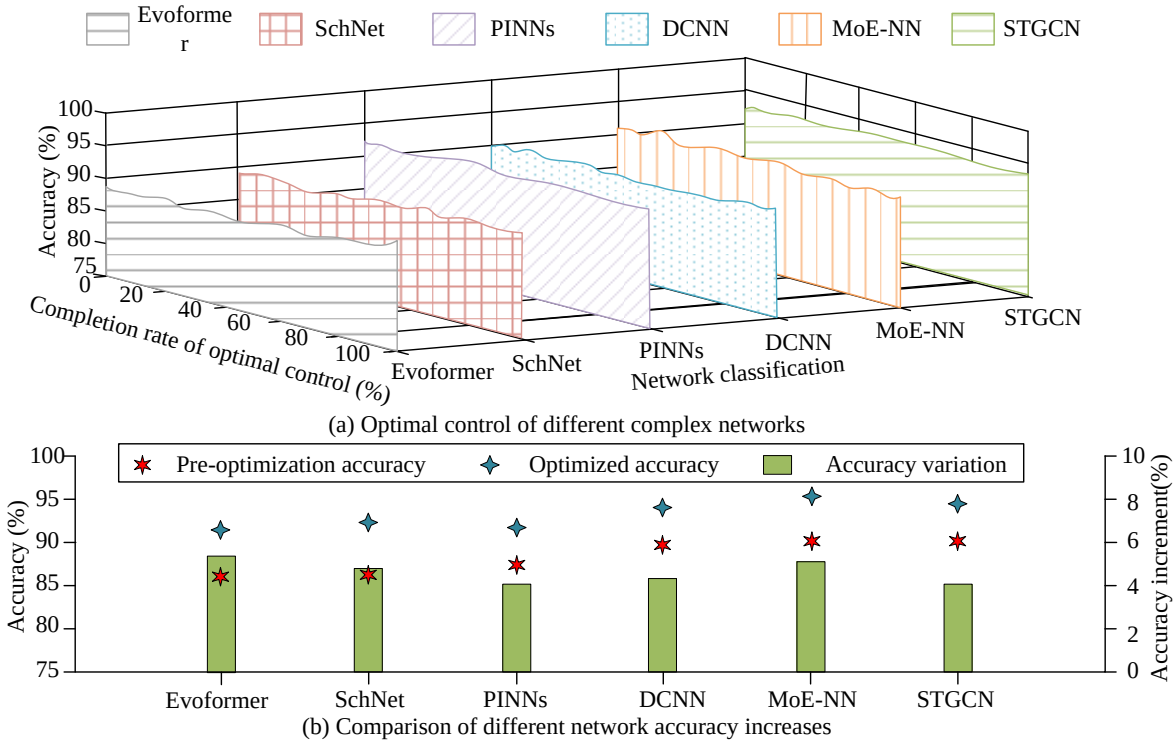


Figure 12: Comparison of average feedback time and average energy consumption.

Temporal Graph Convolutional Network (STGCN) commonly used in the field of transportation. The changes in the accuracy rates of each network are shown in Figure 12.

As shown in Figure 12(a), after optimal control by the KEAI model, the final accuracy of Evoformer was 92.7%, SchNet was 91.8%, PINNs was 89.1%, DCNN was 94.8%, MoE-NN was 94.4%, and STGCN was 93.5%. From Figure 12(b), it can be seen that the accuracy of each model increased after optimal control, with the improvement ranging from 4% to 5%. The average accuracy improvement across all networks was calculated to be 4.7%. This indicates that the KEAI model can be applied to CNs optimal control in different fields and effectively improve the accuracy of the target CNs. Overall, the KEAI model achieved a balance of accuracy, efficiency, and general applicability in the optimal control process of the target CNs, demonstrating strong potential for practical applications. Subsequently, to verify the model performance at different confidence levels, the confidence intervals of the floating-point numbers, parameter quantities, and model sizes of the model for each CN at different confidence levels were compared, as shown in Table 4.

As shown in the table, at different confidence levels, the KEAI model has a good lightweight effect on each target CN, and the floating-point number, parameter quantity and network size of the target CN are all greater than 10%. Moreover, as the confidence level increased, the lightweight effect of the KEAI model on the target network wasalso enhanced, and the confidence interval gradually expands. Among them, when the confidence level was 95%, The floating-point reduction rates of KEAI for Evoformer, SchNet, PINNs, DCNN, MoE-NN and STGCN were 15.1±2.5%, 15.0±1.7%, 13.5±1.9%, 12.5± 1.7%, 18.9 ± 2.4% and 13.6 ± 2.2%, respectively. The parameter reduction for Evoformer, SchNet, PINNs, DCNN, MoE-NN and STGCN was 14.2±2.0%, 14.5± 1.4%, 13.4±1.9%, 12.0±1.5%, 17.5±2.4% and 12.5± 2.0%, respectively. The reduction rates of network size for Evoformer, SchNet, PINNs, DCNN, MoE-NN and STGCN were 13.6±2.4%, 14.1±1.8%, 13.1±1.7%, 12.1± 1.7%, 17.5±2.4% and 13.2±1.8% respectively. The above results indicate that the KEAI model has relatively high credibility.

5 Discussion and conclusion

5.1 Discussion

The KEAI model proposed in the research reduced the floating-point operations, parameter count, and network size of the target network by 14.2%, 14.9% and 15.1% respectively in the test experiment. The lightweight effect was significantly better than that of the comparison models, which was related to the advantage of high accuracy of the core GDPH in the KEAI model. Meanwhile, this wasconsistent with the results in the study of Onken et al. using the optimal control to optimize the lightweight index of the target CN [21]. Furthermore, the accuracy rate of CNN optimized by the KEAI model has increased by 13.4%, further demonstrating that the KEAI model has fully exerted the advantages of GDPH and VIA.

This wassimilar to the result that Chen et al. proposed the optimal control

Table 4: Comparison of the lightweighting effects of the KEAI model under different confidence levels.

/	Confidence level(%)	Evoformer	SchNet	PINNs	DCNN	MoE-NN	STGCN
Floating-point reduction(%)	85	11.1±1.4	13.5±1.2	11.2±1.1	10.5±1.0	16.7±1.6	11.3±1.5
	90	13.2±1.7	14.2±1.4	12.2±1.4	11.2±1.2	17.8±1.8	12.5±1.8
	95	15.1±2.5	15.0±1.7	13.5±1.9	12.5±1.7	18.9±2.4	13.6±2.2
Parameter count reduction(%)	85	12.3±1.6	12.4±1.0	11.1±1.5	10.2±0.9	15.9±1.5	11.2±1.4
	90	13.4±1.9	13.1±1.2	12.4±1.8	11.2±1.2	16.5±2.0	11.4±1.8
	95	14.2±2.0	14.5±1.4	13.4±1.9	12.0±1.5	17.5±2.4	12.5±2.0
Network size reduction(%)	85	11.8±1.5	13.0±1.2	11.5±1.0	10.3±1.1	15.9±1.4	11.5±1.2
	90	12.5±1.8	13.5±1.6	12.4±1.4	11.1±1.4	16.4±1.9	12.0±1.6
	95	13.6±2.4	14.1±1.8	13.1±1.7	12.1±1.7	17.5±2.4	13.2±1.8

technology of human resource CN based on BP network and Logistic regression, which optimally increased the recruitment success rate and training effect by 15% [22]. In the performance verification of the model itself, the processing time and energy consumption of KEAI are much lower than those of the comparison model, indicating that the ETC mechanism and K-means algorithm in the model have played a practical role and reduced the total computational load of the model.

In the practical application test, the KEAI model increased the image recognition accuracy of the YOLOv8 network by 10.2%, indicating that the KEAI model can achieve effective optimal control of the target CN, which wasconsistent with the results obtained by Xie et al. in the study of improving the energy utilization rate of the automotive CN through optimal control [23]. In the applicability test, the KEAI model has improved the accuracy of Evoformer, SchNet, PINNs, DCNN, MoE-NN and STGCN from different fields. Thiswas due to the cluster analysis of the K-means algorithm, which enables the KEAI model to effectively achieve data connection and parameter control for different CNS. Meanwhile, the application of CN and its optimal control in route planning and ship navigation in combination with Wan, and the Santander team's view of the enterprise's business strategy as an example of the CN problem can further illustrate that CN was often used to solve various social practical problems [24-25]. The KEAI model proposed in the research has certain promotion space in reality.

All the above results indicate that the KEAI model proposed in the study integrates the advantages of GDPH, the ETC mechanism, VIA, and the K-means algorithm very well, and obtains an optimal control model that is both fast and accurate.

5.2 Conclusion

To enhance the application efficacy of CNs and facilitate more effective solutions to practical social problems, this study proposes the KEAI model, which takes GDPH as the core structural framework and integrates the K-means algorithm, ETC mechanism, and VIA. Experimental results indicate that the KEAI model significantly outperforms comparative models in both lightweight processing of target CNs and accuracy improvement, while consuming less computational time. Additionally, the KEAI model demonstrates strong generalization capability, enabling its adaptation to target CNs across diverse domains. Overall, the KEAI model optimizes various aspects of CN performance by refining parameters, nodes, and other structural components, ultimately achieving optimal solutions for specific problems and showcasing substantial practical relevance. However, this research was only conducted under stable conditions in the laboratory. The optimal control effect of the target CN under the influence of network failures, unstable flows, dynamic environments, etc., was not considered, nor was the performance of the model under different parameter conditions. Therefore, in future research, experiments can be carried out to address this issue, and the performance of the model in all aspects can be continuously improved.

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Robust Beamforming for Data Correction via Interference-Noise Covariance Reconstruction and Adaptive Error Compensation

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Accurate data detection is an important basis for achieving industrial process operation, performance control, and optimization. In response to the problem of poor accuracy in existing data correction methods, a data correction method based on a matrix reconstruction robust beamforming algorithm is proposed. However, this method still has significant correction errors for the data. Therefore, this study optimizes the matrix reconstruction robust beamforming algorithm to optimize the performance of data correction methods. Simulations were conducted on synthetic nonlinear dynamic data with a sampling frequency of 30 and an SNR of 10 dB. In the simulation results, when the incident angle was 30°, the signal power estimates of traditional beamforming algorithms and the proposed algorithm were 27.57 dB and 30.00 dB, respectively. This indicated that the proposed algorithm could effectively solve the problem of signal power underestimation. Under random error, the reaction concentration state value of the proposed algorithm at a time of 10 seconds was 0.152 J/kg·K, which differed from the true state value by 0.008 J/kg·K. Compared to the RCB baseline, this proposed algorithm reduced the average sum of squared errors and total sum of squared errors by 74.60% and 72.66%, respectively. The results indicate that the proposed algorithm has superior data correction performance. This study has contributed to improving the performance and robustness of beamforming algorithms in practical environments.

Povzetek: Prispevek predstavi izboljšano metodo robustnega oblikovanja smernosti snopa za korekcijo industrijskih podatkov prek rekonstrukcije kovariančne matrike motenj in prilagodljivega modeliranja napak.

1 Introduction

As computer science and artificial intelligence rapidly develop, the process industry has entered the era of informatization. Accurate data detection is a reliable basis for the operation, real-time monitoring and analysis, performance control and optimization, and maintenance and management of the entire industrial production process [1-2]. The accuracy of detection data is the foundation of the operation of all production control systems. However, in the actual detection process, there may be random errors and significant errors, which make the data results inaccurate and unreliable, thereby affecting production operation and increasing the uncontrollability of system operation [3]. Therefore, it is crucial to explore an accurate and efficient data correction method. The beamforming algorithm has been extensively studied by scholars in recent years due to its ability to effectively reduce errors in data correction [4-5].

Yang et al. proposed a robust adaptive beamforming method based on Covariance Matrix Reconstruction (CMR) and subspace decomposition for steering vector estimation and correction. Therefore, the projection method of the signal subspace was corrected, improving the robustness of vector mismatch. This method has achieved good performance in various mismatch situations [6]. Luo et al. designed an effective orthogonal CMR method to remove unwanted signals, addressing the issue of performance degradation in traditional adaptive beamforming algorithms. This method removed useless signals from the received data by constructing a projection matrix, and its performance was superior to traditional methods [7]. Sun et al. developed a nonlinear beamforming method based on an improved efficiency genetic algorithm, aiming to enhance the Signal-to-Noise Ratio (SNR) and achieve effective nonlinear beamforming algorithms. The modified method could effectively enhance the testing of nonlinear beams and had better performance [8]. Yang and Dong developed a robust adaptive beamforming algorithm for steering vector estimation and subspace orthogonal interference power correction to address the performance degradation of Capon beamformers when expected signals appear. This method had good robustness against common mismatch errors [9]. Yu et al. proposed a low complexity receiver for millimeter wave beamforming, beam tracking, and data symbol detection to address the issue of poor accuracy in signal and data detection, aiming to effectively handle dynamic changes. This method could achieve the best spectral efficiency [10].

Due to the poor robustness of traditional beamforming algorithms and certain deficiencies in data correction and signal power estimation, many experts have optimized the performance of related algorithms. Wang et al. proposed

an improved fast iterative shrinkage threshold algorithm for fast compression beamforming to address the issue of high computational complexity in traditional beamforming methods. The method could reduce the amount of floating-point operations by three orders of magnitude [11]. Yang et al. proposed a robust adaptive beamforming method based on CMR and interference power estimation, aiming to reduce the impact of the signal of interest on traditional Capon beamformers and improve the robustness of the algorithm. This method had strong robustness against mismatch errors [12]. Du et al. proposed a robust adaptive beamforming algorithm based on the covariance matrix. This method decomposed the eigenvalues of the reconstructed matrix, derived the correspondence between eigenvalues and power, calculated weight vectors, and proved the effectiveness of the algorithm [13]. Mohammadzadeh et al. designed a robust adaptive beamforming technique for uniform linear arrays based on uncertain regions. This method introduced power estimation based on interference and noise components, and its performance approached the optimal value over a large SNR range [14]. Ge et al. developed a robust adaptive beamforming method based on sparse Bayesian and CMR. It maximized the marginal likelihood function of the data received through the array to accurately estimate the error of data correction. This method could approach the optimal output SNR and has better performance [15]. Table 1 shows the summary of related works.

In summary, numerous scholars have improved the relevant algorithms of beamforming and achieved certain research results. However, the currently advanced Robust Capon Beamforming (RCB) algorithm suffers from significant array position and amplitude/phase errors. In view of this, this study proposes an Interference-Plus-Noise Covariance Matrix Robust Adaptive Beamforming (IPNCM-RAB) algorithm. The algorithm automatically adjusts the column weights to correct the data. In response to the problem of large data correction errors in this method, this study optimizes the performance of the proposed data correction method. The IPNCM-RAB algorithm automatically adjusts the column weights to correct the data. To further enhance the accuracy and robustness of the IPNCM-RAB algorithm, the Array Amplitude Phase Error Correction (AA-PEC) method is integrated.

The research objective is to propose a data correction method based on subspace matrix reconstruction and Robust Beamforming Algorithm (RBA) to improve the accuracy and robustness of data correction. The second objective is to combine AA-PEC to optimize the performance of the proposed algorithm, further reducing correction errors and enhancing the applicability of the algorithm in practical engineering scenarios. The effectiveness of the proposed algorithm has been verified through simulation and comparison with existing methods under various conditions, including linear and nonlinear dynamic data environments. The innovation of this study lies in reconstructing the covariance matrix of interference and noise, which improves the robustness and effectiveness of beamforming algorithms. Then, the AA-PEC method is used to correct the data, minimizing the correction error and improving the application value of the algorithm in practical engineering.

Table 1: Related work summary table

Method	Key Technique	Input Conditions	Dataset Type	Metrics	Limitations	References
CMR-SVEC	Subspace decomposition, SV estimation/correction	SV mismatch, 20dB SNR	Synthetic array	SINR, Robustness	Requires accurate subspace estimation	Yang J et al. [6]
URGLQ	Orthogonal CMR	Strong interference, 15dB SNR	Simulated array	IRR, MSE	Performance drops in dynamic environments	Luo T et al. [7]
GA-Nonlinear	Efficiency-improved genetic algorithm	Nonlinear signals, 10dB SNR	3D seismic data	SNR enhancement	Computationally intensive	Sun Y et al. [8]
Subspace-Ortho	Steering vector estimation via subspace orthogonality	Angle errors, 12dB SNR	Experimental array	SINR, MSE	Limited to small-angle mismatches	Yang H et al. [9]
ML-MMSE	Millimeter-wave beamforming/tracking	Dynamic channels, 5dB SNR	mmWave experimental	Spectral efficiency	Complex implementation	Yu JH et al. [10]
FISTA-Compressive	Modified fast iterative shrinkage-thresholding	High-dimension data	Acoustic array	Computation speed	Requires sparsity assumption	Wang S et al. [11]
CMR-IPE	Covariance reconstruction + interference power estimation	10-25dB SNR	Uniform linear array	SINR, Robustness	Sensitive to interference DOA errors	Yang H et al. [12]
Coprime-IPNCM	Interference-plus-noise matrix reconstruction	Coprime array geometry	Sparse array	Resolution	Restricted to specific array types	Du Y et al. [13]
PSR-UR	Power spectral estimation + uncertainty regions	Wide SNR range	Experimental	Near-optimal SINR	Requires region parameter tuning	Mohammadzadeh S et al. [14]
SBL-CMR	Sparse Bayesian learning + CMR	Low SNR	Simulated	Output SNR, MSE	High computational complexity	Ge S et al. [15]

2 Methods and materials

This section first proposes a data correction method based on matrix reconstruction RBA, which automatically adjusts the array weights to correct the data. To improve the accuracy of data correction, this study proposes a data correction method based on AA-PEC to optimize its performance.

2.1 Data correction method based on subspace matrix reconstruction of RBA

The beamforming algorithm is widely used in the field of array signals due to its ability to accurately correct data errors. In recent years, matrix reconstruction algorithms have developed rapidly due to their strong robustness. However, this algorithm still has certain shortcomings in data correction and source power estimation [16]. Due to the high requirement for prior information of the array in the beamforming algorithm based on matrix reconstruction, it is necessary to provide robustness of the beamforming algorithm under adaptive conditions to achieve accurate data correction. However, existing RCB algorithms suffer from power underestimation and cannot accurately correct data [17]. Therefore, this study designs a data correction method based on the IPNCM-RAB algorithm. This algorithm improves the accuracy of data correction by automatically adjusting the column weights. Figure 1 shows the signal received by a uniform linear array in a subspace matrix.

Figure 1 shows a schematic diagram of a uniform linear array receiving a signal. The figure shows the interaction between the wavefront of a planar wave array and its various elements (Element M-2 to Element 1). Each array element is located on its own normal, which is perpendicular to the reference element of the array. The incident signal reaches the array at an angle θ, resulting in differences in the arrival time of the signal between different elements, where d is the spacing between the elements. This study applies $Q+1$ signals with a center frequency of f_s to a uniform front line, where the uniform front line consists of M elements. At time t, the signal received by the array element is as shown in equation (1).

$$x_m(t) = \sum_{q=0}^{Q} s_q(t-\tau_{mq}) + n_m(t) \tag{1}$$

In equation (1), $x_m(t)$ is the signal received by the m-th element. $s_q(t)$ is the complex envelope vector and $n_m(t)$ is the noise in the element space. τ_{mq} is the delay between the signal received by the m-th element and the reference element. When the distance difference between signals reaching adjacent array elements is $d\sin\theta_q$, the matrix representation of the received signals in the array is as shown in equation (2).

$$\begin{cases} \tau_{mq} = \dfrac{(m-1)d\sin\theta_q}{c} \\ x(t) = \sum_{q=0}^{Q} s_q(t)a_q + n(t) = AS(t) + n(t) \end{cases} \tag{2}$$

In equation (2), $d\sin\theta_q$ is the difference in signal arrival distance. c means the speed of light. $x(t)$ is the matrix of the array received signal model. a_q means the guiding vector of the q-th incident source. A is an array manifold matrix. $n(t)$ is a noise vector. $S(t)$ means the complex envelope vector of the incident signal. The beamformer weights and sums the signals received by the array based on the spatial information of different incident signals. The schematic diagram of its beamforming and uniform linear array robust beamformer is shown in Figure 2.

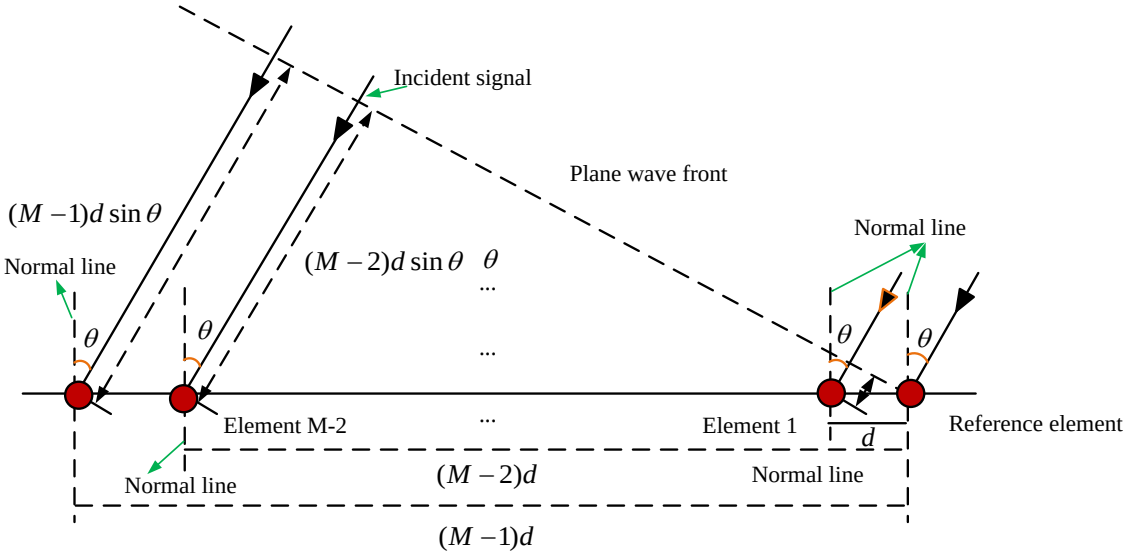
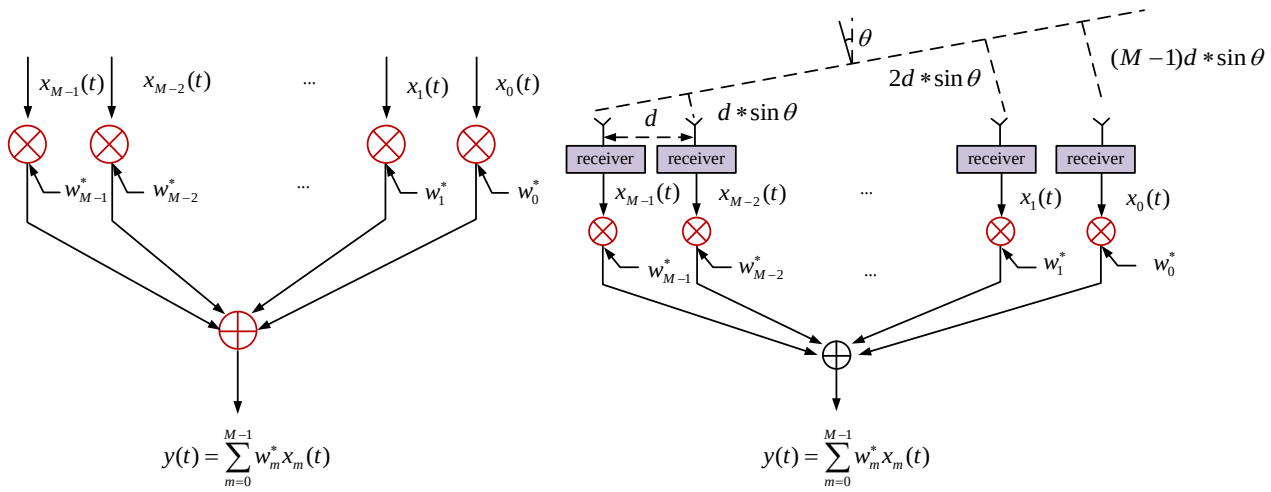


Figure 1: Uniform linear array receiving signal schematic.



(a) Beam alignment diagram

(b) Uniform linear array robust beam synthesizer diagram

Figure 2: Diagram of beamforming and uniform linear array robust beamformers.

In Figure 2 (a), the signals $x_{M-2}(T)$ to $x_0(T)$ received by each element in the array are weighted by their respective weights w^*_{M-2} to w^*_0 and summed to form the output signal $y(t)$. In Figure 2 (b), each received signal is also weighted, but to adapt to the incident angle θ, the time difference of signal arrival is also considered. The impact of different path lengths on the signal, such as $d\cdot\sin\theta$ and $2d\cdot\sin\theta$, is marked in the figure, and these differences are compensated for by weight adjustment to optimize the beamforming effect. The robust estimation of beamforming algorithms mainly relies on data regression theory. An unbiased estimation function using data regression theory is designed. This function can effectively complete data correction under the condition of insensitivity to data bias, thereby obtaining coordinated data that is closer to the measured values [18]. The impact function is a core indicator function in robust estimation, which can display the importance and impact of various estimation errors. Its calculation is shown in equation (3).

$$I(\xi_0)=\lim_{t\to 0}\frac{T\left[(1-t)f+t\delta(\xi-\xi_0)\right]-T\left[f\right]}{t} \tag{3}$$

In equation (3), $I(\xi_0)$ is the impact function of robust estimation. $\delta(\xi-\xi_0)$ is the particle distribution function centered around ξ_0. T is a robust function. $\{\xi_1,\ldots\xi_n\}$ follows a distribution function. ξ_0 is the effect function of robust estimation. The impact function quantifies the degree to which an estimate is affected by outliers or deviations from the expected data distribution. This function is crucial for understanding how robust estimators minimize the impact of outliers. The expression of the influence function at the data point and the expression of the joint weight function are denoted in equation (4).

$$\begin{cases} I(\xi_i)=\dfrac{d\rho}{d\xi_i} \\ W(\xi_i)=\dfrac{I(\xi_i)}{\xi_i} \end{cases} \tag{4}$$

In equation (4), $I(\xi_i)$ is the influence function at point i of the data band. $W(\xi_i)$ is a joint weight function. ξ_i is the measurement error value at data point i. ρ is the objective function. The joint weight function combines the deviation of the influence function from the mean, providing a measure of the relative importance of each data point in the estimation process. This helps to understand how each data point contributes to the robustness of the overall estimation. According to the theory of robust estimation, a robust estimation function $\rho(x)$ is designed, which is expressed as equation (5) [19].

$$I(x)=\frac{d\rho(x)}{dx}=\begin{cases}-e^{-x}x^2+2xe^{-x}+c(1-e^{-x})+cxe^{-x}, x\geq 0\\ e^{-x}x^2+2xe^{-x}+c(1-e^{-x})+cx(-e^{x}), x<0\end{cases} \tag{5}$$

In equation (5), $I(x)$ is the influence function of the robust estimation objective function. x is the standard error. c is an adjustable parameter. This function minimizes the sum of robust function values to ensure that the estimation results are less affected by outliers. This is a key step in developing robust estimators that can effectively handle noisy or contaminated data. To investigate the impact of interference power estimation on RBA, this study analyzes the Interference Rejection Ratio (IRR). The calculation of the i -th IRR is given by equation (6).

$$\frac{\sigma_i^2}{\sigma_{io}^2}=\frac{E\{|s_i(k)|^2\}}{E\{|w^H a_i s_i(k)|^2\}}=\frac{E\{|s_i(k)|^2\}}{\mu^2|a_0 R_{i+n}^{-1}a_i|^2 E\{|s_i(k)|^2\}} \tag{6}$$

In equation (6), σ_i^2 is the output power of interference. σ_{io}^2 is the output power of the beamforming system. $s_i(k)$ is the complex envelope vector of the i -th interference. a_0 is the expected signal. μ is a constant. a_i is the i -th interference signal. R_{i+n}^{-1} is the corresponding covariance matrix. The higher the IRR value, the better the suppression effect on interference, which is crucial for maintaining the integrity of the expected signal in strong interference environments. Finally, based on the obtained noise power estimation, the

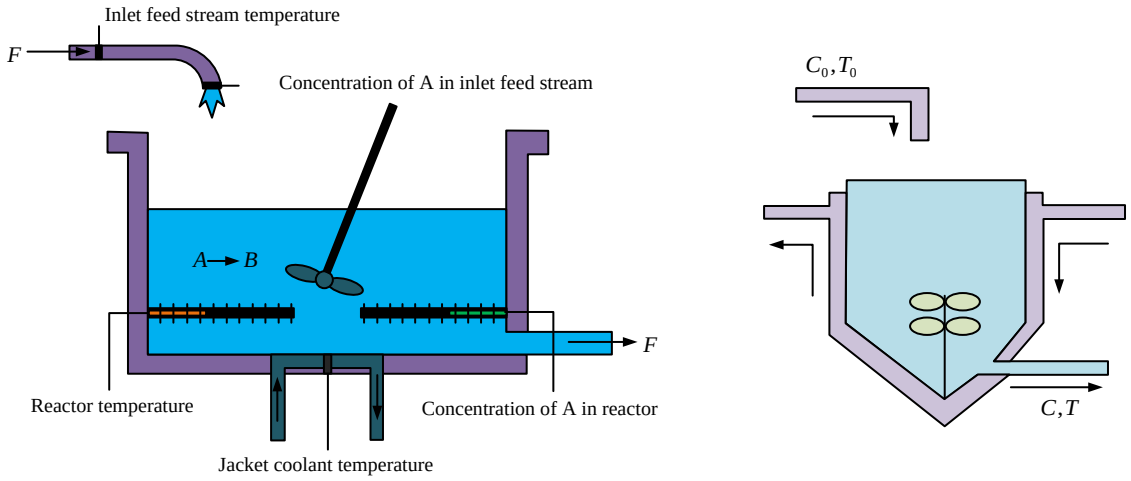
interference plus noise covariance matrix is reconstructed. The expression and weight vector of the beamforming algorithm are shown in equation (7).

$$\begin{cases} \hat{R}_{i+n} = \sum_{q=1}^{Q} \hat{\sigma}_q^2 \hat{a}(\theta_q)\hat{a}(\theta_q)^H + \hat{\sigma}_n^2 I \\ w_{IPNCM} = \dfrac{\hat{R}_{i+n}^{-1}\hat{a}(\theta_0)}{\hat{a}(\theta_0)^H \hat{R}_{i+n}^{-1}\hat{a}(\theta_0)} \end{cases} \tag{7}$$

In equation (7), $\hat{R}_{i+n}^{-1}$ is the inverse matrix of the corresponding covariance matrix. w_{IPNCM} is the weight vector of the beamforming algorithm. Q is the signal that reaches the array. σ_q^2 means the output power of the q-th interference. The weight vector of beamforming algorithm optimizes beamforming performance by minimizing interference and noise while maximizing the signal of interest. This study enhances the robustness of the beamforming algorithm by obtaining weight vectors, thereby improving the accuracy of the algorithm for data correction. To further improve the accuracy and robustness of the IPNCM-RAB algorithm, several variants of the IPNCM algorithm are developed and compared, including IPNCM-cor, IPNCM-sub, IPNCM-qcqp, and IPNCM-ortho. These variants use different techniques to reconstruct the interference plus noise covariance matrix. Among them, IPNCM-cor focuses on using correlation-based methods to correct the covariance matrix of interference and noise. By utilizing the correlation between estimated interference components and noise components, this method improves the accuracy of the reconstructed matrix. This method ensures that the covariance matrix better represents the actual interference and noise conditions, thereby improving the robustness of the beamforming algorithm. IPNCM-sub uses subtraction-based techniques to estimate and remove interference components from the noise covariance matrix. By accurately removing interfering components, the remaining noise covariance matrix becomes more accurate, resulting in better performance in data correction and signal estimation. IPNCM-qcqp utilizes the Quadratic Constrained Quadratic Programming (QCQP) method to optimize the reconstruction of the interference plus noise covariance matrix. The QCQP method ensures that the reconstructed matrix satisfies specific constraints, such as positive definiteness and orthogonality, which are crucial for the robustness and accuracy of beamforming algorithms. IPNCM-ortho introduces an orthogonalization process to ensure that the interference component is orthogonal to the signal component. By enforcing orthogonality, the algorithm can more effectively separate the expected signal from interference, thereby improving the robustness and accuracy of beamforming algorithms. For the correction of dynamic data, this study adopts the Dynamic System Model (DSM) as the constraint equation to achieve data correction. DSM is typically represented using time-varying state variable functions. DSM's data correction utilizes the time redundancy feature to correct real-time read data [20]. In the process of correcting nonlinear dynamic data, this study optimizes the constraint conditions of the dynamic model, as shown in equation (8).

$$\begin{cases} \min \Phi = \sum_{k=0}^{c} \left[\hat{x}(t_k) - \tilde{x}(t_k)\right] \sum^{-1} \left[\hat{x}(t_k) - \tilde{x}(t_k)\right] \\ s.t.\, f\left(\dfrac{d\hat{x}(t)}{dt}, \hat{x}(t)\right) = 0 \\ h(\hat{x}(t)) = 0 \\ g(\hat{x}(t)) < 0 \end{cases} \tag{8}$$

In equation (8), $\min \Phi$ is the estimated minimum deviation of the measured value. c is the current time. k is the sampling time. Σ is the covariance matrix. $\hat{x}(t)$ is the estimation function. $\hat{x}(t_k)$ is the value of the estimated function at time t_k. $\tilde{x}(t_k)$ is the measurement value at time t_k. f is a differential constraint equation. h and g are equality constraints, including upper and lower bounds on variables. The DSM ensures that the corrected data are consistent with the expected behavior of the system over time, which is crucial for accurate real-time data processing. To further validate the effectiveness of the proposed RBA in practical applications, the Continuous Stirred Tank Reactor (CSTR) model is employed as a dynamic system framework to simulate real-time data correction. The CSTR model provides a practical testing platform for evaluating the performance of algorithms in correcting dynamic data, ensuring that the robustness and accuracy proven in theoretical development can be effectively translated into practical scenarios. This study uses a CSTR-DSM to calibrate dynamic data. Figure 3 shows the framework of the model [21]. In Figure 3 (b), C_0 and T_0 are input variables, where C_0 is the system feed concentration and T_0 is the system feed temperature. C and T are state variables, representing the system output concentration and temperature, respectively. Based on chemical kinetics and thermodynamics, the mass differential equation and thermal differential equation for the DSM of CSTR are designed. The concentration and temperature are dimensionless relative concentrations and temperatures.



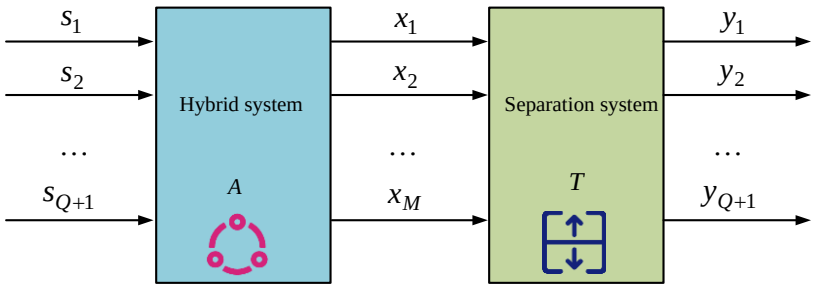
(a) Continuous stirred tank system model diagram (b) CSTR system model structure diagram

Figure 3: Schematic diagram of dynamic model of CSTR

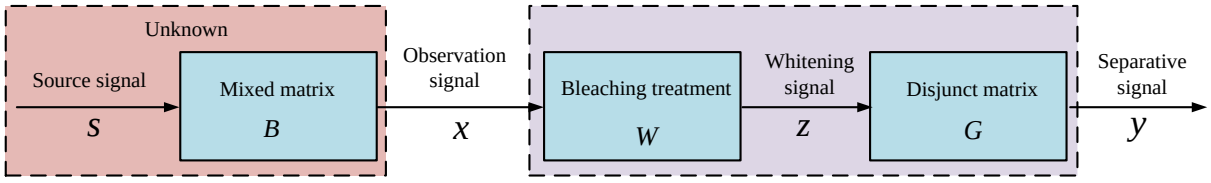
Figure 3 (a) shows the material flow and reaction process inside the reactor, where A and B represent reactants, F represents feed stream, and the reactor temperature and feed stream temperature are indicated separately. The figure also shows the concentration changes of A inside the reactor. Figure 3 (b) shows the external structure of the reactor, including the jacket coolant temperatures Ca, Ta, and the fluid temperatures C,T inside the reactor. These graphs are used to design the mass differential equation and thermal differential equation of CSTR-DSM for simulating and analyzing the behavior of the reactor under different operating conditions. The concentration and temperature are dimensionless relative values.

2.2 Performance optimization of data correction method based on AA-PEC

The data correction method based on matrix reconstruction RBA still has defects such as large correction errors and poor accuracy when correcting data. Therefore, it is necessary to provide robustness of beamforming algorithms under adaptive conditions to achieve accurate data correction. The traditional beamforming algorithm suffers from significant errors in the direction of incoming waves, array position, and amplitude and phase, leading to a decline in its performance. Therefore, it is necessary to optimize the performance of data correction methods [22]. The AA-PEC method is mainly used to correct amplitude and phase errors in data. After initial calibration by AA-PEC, DSM serves as the validator for evaluating the accuracy and reliability of the calibration data. DSM models the dynamic behavior of the system using time-varying state variable functions and compares the corrected data with the expected system performance for verification. This two-stage process ensures the accuracy and robustness of data correction. The AA-PEC method aims to optimize the performance of the data correction method for matrix reconstruction beamforming algorithm. This method introduces blind source separation theory into beamforming algorithms to estimate amplitude and phase errors, and finally reconstructs the covariance matrix of interference and noise to improve the accuracy of data correction. The AA-PEC method is used to correct amplitude and phase errors in data, thereby improving the overall accuracy and robustness of the IPNCM-RAB algorithm. Assuming that the mixed system through which source signal s passes is A, the array system consists of M elements, and the received replacement measurement data are $x = [x_1, x_2, \ldots, x_M]^T$ [23]. In this study, the separation system T designed using Independent Component Analysis (ICA) is used to process the observed data, and the output data of the source signal are $y = [y_1, y_2, \ldots, y_{Q+1}]^T$ [24]. The number of independent sources is determined based on the complexity of the signal mixture and the specific application requirements. In this study, the number of independent sources is set to n, which is determined through preliminary analysis of the signal data. The convergence criteria for the ICA algorithm are based on the stability of the estimated independent components. The algorithm iterates until the change in the estimated components is below a predefined threshold, which is set to 10−5 in this study. This ensures that the algorithm reaches a stable solution without unnecessary computation. Figure 4 shows the models of the hybrid system and the separation system, as well as the structure of the blind source separation system.



(a) Hybrid system and separate system model diagram



(b) Diagram of blind source separation system

Figure 4: Hybrid and separation system model and blind source separation system diagram.

Figure 4 (a) shows the model diagrams of the hybrid system and the separation system. Multiple source signals s_1 to s_{Q+1} enter the hybrid system through the mixing matrix A, generate observation signals x_1 to x_M, and then obtain separated signals y_1 to y_{Q+1} through the separation system T. Figure 4 (b) provides a detailed description of the blind signal separation process, including the unknown signal mixing process and the blind signal separation process. The source signal S generates the observation signal x through the mixing matrix B, undergoes whitening processing W and whitening signal Z, and then obtains the separated signal y through the separation matrix G. In the process of signal mixing and separation, the received signal at time k and the observed data output by the separation system are shown in equation (9).

$$\begin{cases} x_m(k) = \sum_{i=0}^{Q} a_{mi} s_i(k), m = 1,2,\ldots,M \\ Y(k) = TX(k) = TAS(k) \end{cases} \tag{9}$$

In equation (9), $y_m(k)$ is the m-th signal received at time k. $Y(k)$ is the output observation data. a_{mi} is the mixing coefficient. S is the input signal. X is observational data. This study uses the ICA algorithm to preprocess the observation data X to remove redundant information. This equation represents the mixing process of the source signal and the subsequent separation using the ICA algorithm. This is the fundamental step in separating various signals from a mixed signal environment. To further obtain the source signal, this study constructs a whitening matrix. The whitening process is a crucial step in the ICA algorithm. It involves converting observational data into a form with a unit covariance matrix. This method achieves this by calculating the eigenvalue decomposition of the covariance matrix of the observed data. This process ensures that the data are uncorrelated and have unit variance, thereby simplifying subsequent ICA processing. Its whitening process is shown in equation (10) [25].

$$\begin{cases} R = U\Lambda U^H = U\Lambda^{\frac{1}{2}}\Lambda^{\frac{1}{2}}U^H \\ W = \Lambda^{\frac{1}{2}}U^H \end{cases} \tag{10}$$

In equation (10), W is the whitening matrix. R is the covariance matrix. $\Lambda = diag\{\lambda_1, \lambda_1, \ldots, \lambda_M\}$ is a diagonal matrix. λ is the eigenvalue of R. U is a feature matrix composed of the eigenvectors of R. The whitening matrix process ensures that the data are uncorrelated and have unit variance, thereby simplifying subsequent ICA processing. To achieve the design of the separation matrix, this study uses the Joint Approximation Diagonization of Eigenmatrices (JADE) algorithm to diagonalize the constructed cumulant matrix, as shown in equation (11) [26].

$$\begin{cases} q_{ij} = \sum_{l=0}^{Q}\sum_{k=0}^{Q} cum(z_i, z_j^*, z_k, z_l^*) e_{kl}, i, j = 1,2,\ldots,Q+1 \\ T = A^{-1} = U^H W \end{cases} \tag{11}$$

In equation (11), q_{ij} is the weighted sum of the cumulative matrix $cum(z_i, z_j^*, z_k, z_l^*)$ with weight e_{kl}. T is the separation matrix. JADE is a powerful tool in blind source separation, especially when the number of sources and mixtures is equal. JADE is chosen because it has robustness in handling complex mixed signals and can effectively separate signals even if the number of signal sources is equal to the number of mixed signals. This algorithm is particularly advantageous in scenarios where precise knowledge of the array manifold is limited, as it can operate without requiring detailed calibration data. The JADE algorithm's ability to handle multiple signals and its robustness against noise make it an ideal choice for improving the accuracy of amplitude and phase error corrections in the proposed method. The assumptions of

sparsity and independence directly impact the reliability of real-time corrections. Sparse and independent signals are more likely to be accurately separated and corrected in real-time. This is because the ICA algorithm can more effectively identify and isolate the relevant components of the signal, leading to more accurate and reliable corrections. On the contrary, if the signal is not sparse or independent, the separation process may introduce errors that propagate and affect the reliability of the correction. The IPNCM algorithm is sensitive to array prior information. Therefore, under the condition of array correction error, this study adopts the JADE algorithm to process the received signal, to improve the robustness of the beamforming algorithm [27], as shown in equation (12).

$$\begin{cases} Y(k) = GBS(k) = GTAS(k) \\ B = TA \end{cases} \tag{12}$$

In equation (12), B is a mixed matrix. T is the amplitude phase error matrix. G is the separation matrix. This matrix represents the combined amplitude and phase error of each array element. This matrix is crucial for correcting amplitude and phase errors in the received signal, which can improve the overall accuracy of the system. The final received signal separation is shown in equation (13).

$$\hat{X}(k) = \hat{B}\hat{S}(k) \tag{13}$$

In equation (13), $\hat{X}(k)$ is the received separated signal. This equation represents the final result of separating the source signal from the mixed data. This step is crucial for obtaining various source signals that can be further processed or analyzed. The amplitude and phase error matrix is given by equation (14).

$$\hat{T}_{m,m} = \mathrm{diag}(g_1 e^{-j\phi_1}, g_2 e^{-j\phi_2}, \ldots, g_m e^{-j\phi_m}) \tag{14}$$

In equation (14), $\hat{T}_{m,m}$ is the amplitude phase error matrix. g_m is the estimated amplitude error value of the m-th element. ϕ_m is the phase error of the m-th element. The amplitude phase error matrix represents the combined amplitude and phase errors of each array element. This matrix is crucial for correcting amplitude and phase errors in the received signal, which can improve the overall accuracy of the system. The flowchart of data correction based on matrix reconstruction RBA is shown in Figure 5.

In Figure 5, the process starts from the input of the original array and goes through signal acquisition and data preprocessing (including covariance matrix decomposition and JADE diagonalization). The core processing includes IPNCM reconstruction, interference power estimation, CMR, and AA-PEC correction. Finally, beamforming and weight vector calculation are performed to output the corrected data.

The time complexity of the proposed method primarily depends on the eigenvalue decomposition and the matrix inversion operations involved in the beamforming process. The eigenvalue decomposition of an N×N matrix typically has a time complexity of $O(N^3)$, where N is the number of elements in the array. Therefore, the overall time complexity of the proposed method can be estimated as $O(N^3)$. Assuming that the number of sources M is much less than N and can be considered constant. The space complexity is determined by the amount of memory required to store the input data and intermediate results. The main memory consumers are the received signal matrix X, the covariance matrix R_x, the eigenvector matrix U, and the steering vectors ai. The received signal matrix X requires $O(NM)$ space, where M is the number of snapshots. The covariance matrix R_x and the eigenvector matrix U each require $O(N^2)$ space. The steering vectors a_i require $O(NM)$ space. Therefore, the overall space complexity of the proposed method is $O(N^2 + NM)$, which simplifies to $O(N^2)$ when M is considered constant.

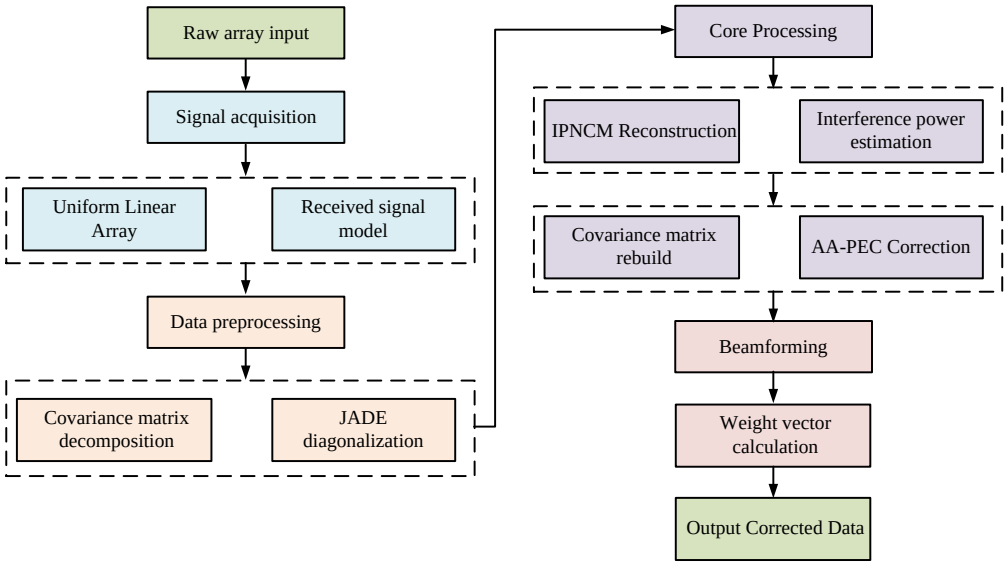


Figure 5: Flow chart of data correction and performance optimization based on matrix reconstruction RBA.

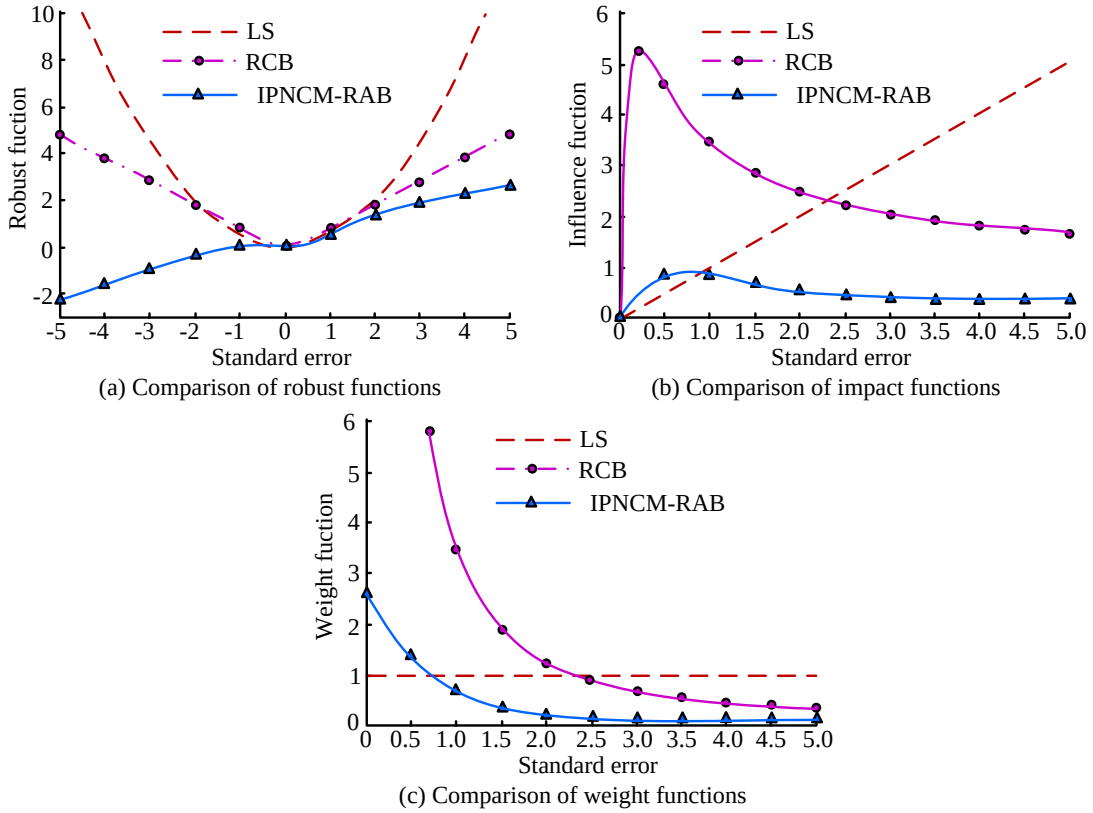
3 Results

This section first analyzes the data correction results of matrix reconstruction RBA. After optimizing the performance of the data correction algorithm, this study analyzes the accuracy of the algorithm's data correction under random and significant errors through simulation experiments.

3.1 Analysis of data correction results based on matrix reconstruction RBA

This study conducts simulation experiments using MATLAB software. The Signal-to-Interference plus Noise Ratio (SINR) is 30dB, the sampling frequency is 30, and the SNR is 10dB. In the experiment, the sampling angle intervals for IPNCM-cor and IPNCM-sub are 1° and 0.5°. The sampling angle interval between IPNCM-qcqp and IPNCM-ortho is 0.1°. The synthetic data used in these simulations are generated based on a Gaussian distribution assumption for the noise and signal components. This is a common practice in signal processing simulations to model real-world noise characteristics. The SNR is set to 10 dB, which is a typical value used in many beamforming studies to represent moderate noise conditions. This SNR level is chosen to ensure that the signal is detectable but still significantly affected by noise, making it a challenging yet realistic scenario for evaluating the performance of the proposed algorithm. The source signals are modeled as sinusoidal waves with varying frequencies to simulate different signal sources. This choice is justified as sinusoidal signals are fundamental in many practical applications and can effectively test the robustness of the beamforming algorithm.

The experiment compares the robustness functions, influence functions, and weight functions of Least Squares (LS), RCB, and the proposed algorithm (IPNCM-RAB) to explore the robustness, as shown in Figure 6. In Figure 6 (a), when the standard error is 4, the robust functions of LS, RCB, and the proposed algorithm are 8.25, 3.90, and 2.05. In Figure 6 (b), when the standard error is 0.5, the influence functions of LS, RCB, and the proposed algorithm are 5.21, 0.45, and 0.98. The proposed algorithm is closer to the influence function of LS. In Figure 6 (c), when the standard error is 1, the weight functions of LS, RCB, and IPNCM-RAB algorithms are 1.00, 3.47, and 0.85. The proposed algorithm is closer to the weight function of LS. This indicates that IPNCM-RAB has good performance in suppressing outlier errors and is robust.

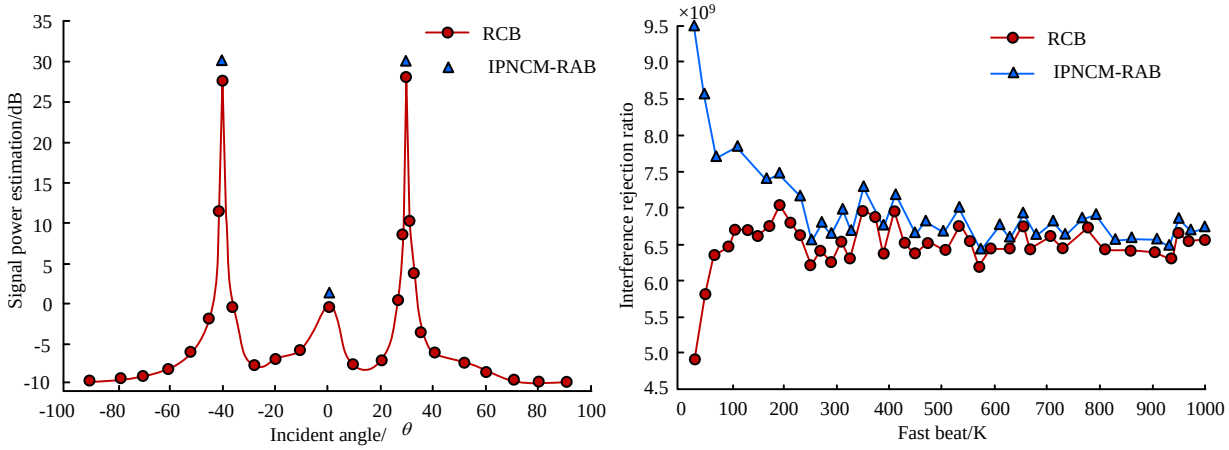


(a) Comparison of robust functions

(b) Comparison of impact functions

(c) Comparison of weight functions

Figure 6: Comparison of robust functions, influence functions, and weight functions.



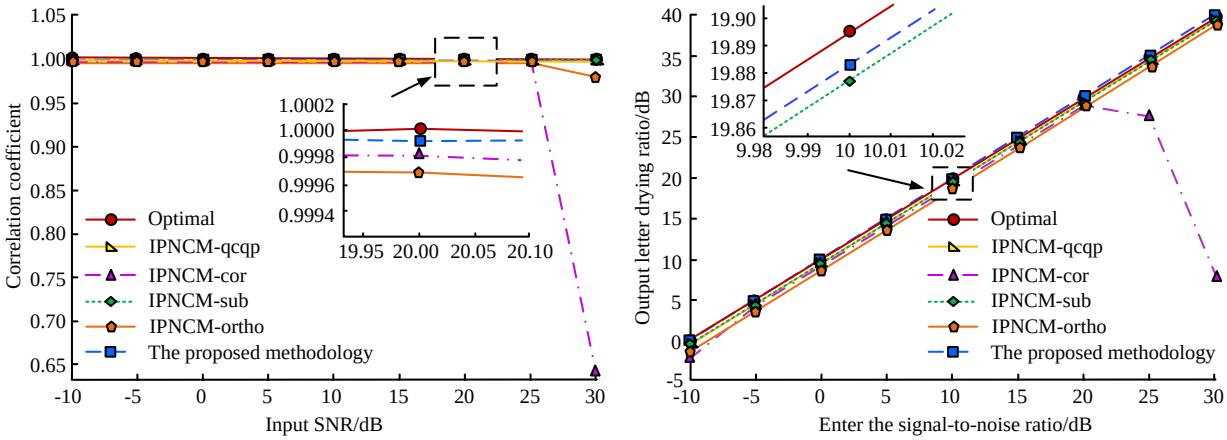
(a) Signal power underestimation improves results

(b) Comparison of interference rejection ratio

Figure 7: Comparison of signal power underestimation improvement results and IRR.

Figure 7 compares the signal power estimation and IRR of IPNCM-RAB and RCB to explore the improvement of subspace matrix-based RBA on power underestimation. In Figure 7 (a), when the incident angle of the signal is -40°, the estimated signal power of RCB and the proposed algorithm are 27.10 dB and 30.05 dB. When the incident angle is 0° and 30°, the signal power estimates of RCB and the proposed algorithm are 0.00 dB and 27.57 dB, 1.02 dB and 30.00dB. In Figure 7 (b), when the number of snapshots is 30, the IRRs of RCB and IPNCM-RAB are 4.9×109 and 9.5×109. When the number of snapshots reaches 780, the IRR of RCB is 6.6×109, and the proposed algorithm is 6.9×109. This indicates that the proposed RBA can effectively solve the problem of signal power underestimation and improve IRR in small block shooting situations.

To evaluate the accuracy of the reconstructed matrix, this study analyzes the correlation coefficient between theoretical IPNCM and reconstructed IPNCM through the variation of input SNR. In addition, the relationship between the input SNR and output SINR of the proposed algorithm is explored when there is angle error mismatch, as shown in Figure 8. In Figure 8 (a), when the input SNR is 20dB, the correlation coefficients of IPNCM-cor and IPNCM-orthor are 0.9998 and 0.9997. The correlation coefficient of the research model is 0.9999, which is closer to the optimal algorithm, indicating that the reconstructed IPNCM by this algorithm is more accurate. In Figure 8 (b), when the input SNR is 10 dB, the output SINR of IPNCM-sub is 19.878 dB, and the proposed algorithm is 19.882. The output SINR of the latter is closer to the optimal algorithm, indicating that the performance of the improved algorithm is closer to the optimal algorithm.



(a) The correlation coefficients between IPNCM and theoretical IPNCM were reconstructed

(b) Relation between output SINR and input SNR when Angle error is mismatched

Figure 8: The correlation coefficient and angle error matching degree of different algorithms under SNR and SINR.

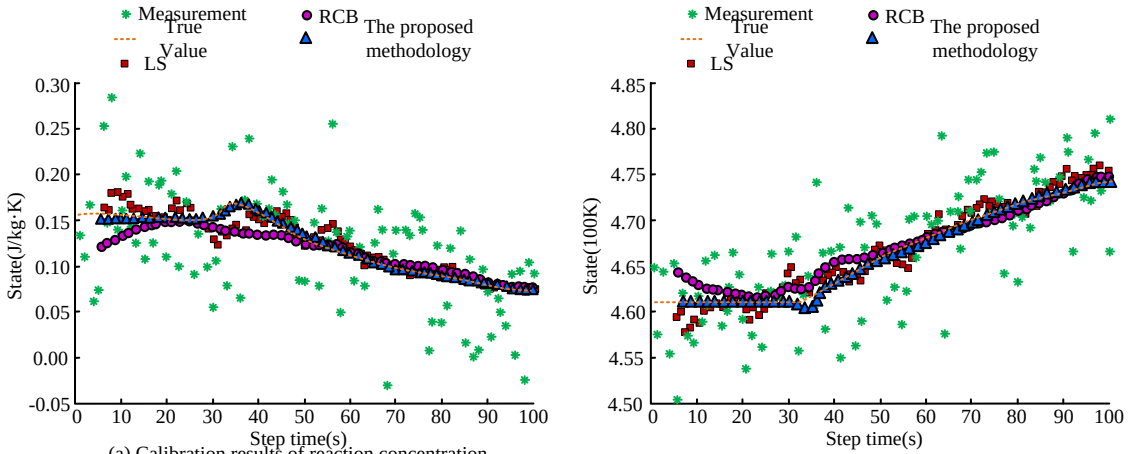
3.2 Analysis of simulation results of data correction for optimizing algorithm performance

In the correction of dynamic data, T_0 is set to 3.5, C_0 to 6.5, T to 4.6091, and C to 0.1531. The sampling quantity is 100 and the sampling interval is 2.5 seconds. At the 30th sampling point of concentration, the sampling value is 6.5-7.5. The simulation experiment is divided into two environments, random error and total error value with specific sampling time points added. 100 samples are used in the simulations. This number is chosen to balance computational complexity and the need for sufficient data

points to accurately capture the dynamic behavior of the system. The sampling interval is set to 2.5 seconds. This interval ensures that the system dynamics are adequately captured without overwhelming computational resources. The incident angles are chosen as ±30°. These angles are selected to represent typical off-axis scenarios in beamforming applications and to test the algorithm's performance in handling signals arriving from different directions. The SNR is set to 10 dB, which is a moderate level of noise interference. This value ensures that the simulations reflect realistic conditions where the signal is detectable but still significantly affected by noise.

Figure 9 shows the simulation results analysis of different algorithms under random errors to explore the data correction effect of the proposed algorithm. In Figure 9 (a), when the time is 10 seconds, the reaction concentration state values of LS and RCB are 0.176 J/kg·K and 0.125 J/kg·K. Compared with it, the state value of the proposed algorithm is 0.152 J/kg·K, which differs from the true state value by 0.008 J/kg·K. When the time reaches 40 seconds, the true state value of the reaction concentration is 0.158 J/kg·K. The state values of the three algorithms are 0.147 J/kg·K, 0.132 J/kg·K, and 0.160 J/kg·K, respectively. In Figure 9 (b), at a time of 30 seconds, the true reaction temperature state value is 4.610, and the state values of LS and RCB are 4.651 and 4.632. The state value of the proposed algorithm is 4.608. Compared with the actual value, the reaction temperature state value of this algorithm only decreased by 0.002. The proposed algorithm can accurately correct data under random errors, proving its feasibility.

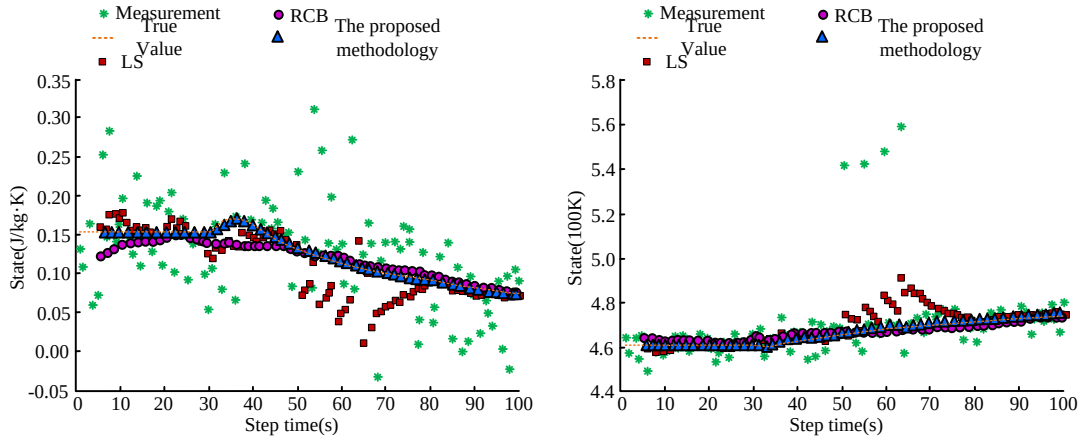
Figure 10 further validates the accuracy of the proposed algorithm for data correction. This study analyzed the results under significant errors. In Figure 10 (a), when the time is 35 seconds, the reaction concentration state values of LS, RCB, and the proposed algorithm are 0.138 J/kg·K, 0.142 J/kg·K, and 0.171 J/kg·K, respectively, and the true state value is 0.170 J/kg·K. When the time reaches 70 seconds, the true reaction concentration state value is 0.112 J/kg·K. The state values of LS, RCB, and the proposed algorithm are 0.075 J/kg·K, 0.124 J/kg·K, and 0.114 J/kg·K. This indicates that under significant errors, the reaction concentration state values of the proposed algorithm are closer to reality. In Figure 10 (b), when the time is 70 seconds, the reaction temperature state values of RCB and IPNCM-RAB are 4.605 and 4.610. Compared to that, the proposed algorithm reduces by 0.001. The proposed algorithm shows that the state value of the temperature response under significant error is closer to the true state value, proving its accuracy.



(a) Calibration results of reaction concentration data

(b) Reaction temperature data correction results

Figure 9: Correction results of reaction concentration and temperature data under random error.



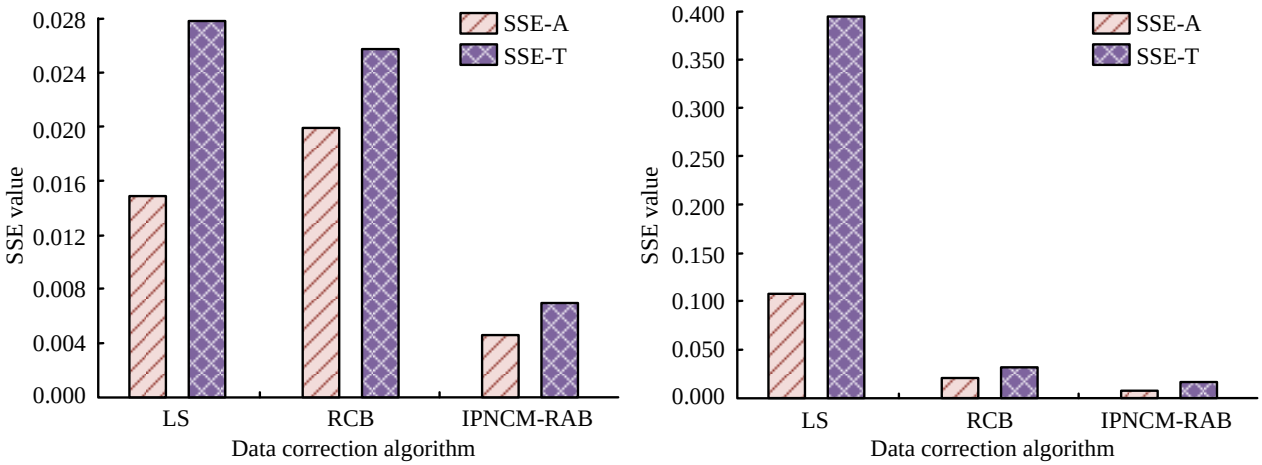
(b) Reaction temperature data correction results

(b) Reaction temperature data correction results

Figure 10: Correction results of reaction concentration and temperature data under significant error.

This study compares the Sum of Squared Errors (SSE) of three algorithms, LS, RCB, and IPNCM-RAB, under the superposition of random and coarse errors, as shown in Figure 11. In Figure 11 (a), under random error, the average SSE of RCB and IPNCM-RAB are 0.0181 and 0.0048, and the total SSE is 0.0267 and 0.0073. Compared with LS and RCB, the average SSE of the proposed algorithm decreases by 68.0% and 74.60%, and the total SSE decreases by 73.93% and 72.66%. In Figure 11 (b), under the condition of coarse error superposition, the average SSE of the three algorithms is 0.1168, 0.0181, and 0.0048, and the total SSE is 0.387, 0.0255, and 0.0073. The proposed algorithm has the smallest SSE value under the combined systematic and random errors, and the data correction results are more inclined towards the true values, indicating that the algorithm has better data correction performance.

To demonstrate the data correction effect of the proposed algorithm, this study corrects the erroneous data through simulation examples of linear and nonlinear systems, and compared the data correction results of the algorithm and RCB. Table 2 shows the data correction for linear systems. In the linear system experiment, the data correction SSE values for RCB and the proposed algorithm are 702.1268 and 1.9×10-5. The data correction results of the proposed algorithm are closest to the true values, indicating that it has a good data correction effect.



(a) SSE values of different data correction algorithms under random errors

(b) SSE values of different data correction algorithms under coarse error superposition

Figure 11: Comparison of SSE values of different data correction algorithms under random error and coarse error superposition.

Table 2: Data correction results for linear systems

Flowing stock	True value (mol/L)	Measurement value (mol/L)	RCB correction	IPNCM-RAB correction	Deviation from Ground Truth (%)
1	3564.230	3542.760	3550.806	3564.200	0.001
2	1828.620	1810.890	1808.625	1828.600	0.001
3	1735.610	1744.170	1742.181	1735.600	0.001
4	2806.900	2653.810	2796.404	2806.900	0.000
5	723.803	680.050	720.912	723.800	0.000
6	25.930	25.910	25.910	25.900	0.116
7	7.600	7.580	7.580	7.600	0.000
8	111.979	112.754	112.747	112.00	0.019
9	2694.920	2696.270	2683.657	2694.900	0.001
10	58.750	58.400	58.390	58.700	0.085
SSE	/	/	702.1268	1.9000e-005	/

Table 3 shows the data correction results for nonlinear systems. Among them, the data correction SSE values for RCB and the proposed algorithm are 0.0021 and 7.1412×10-8. Therefore, in the experiment of studying algorithms in nonlinear systems, their data correction results are closer to the true values, indicating that they have good data correction performance.

To comprehensively compare with other advanced models, Table 4 summarizes the performance metrics of IPNCM-RAB and AA-PEC methods (proposed method) with other advanced models such as Deep Learning Denoiser, Probabilistic Filter, Transformer-based Signal Enhancement method, and Traditional RCB method. The study conducts 10 repeated experiments, and the results indicate that the proposed method has the lowest average SSE of 0.0048 and SNR of 30.27. The average SSE of the traditional RCB method is the highest at 0.0181, and the SNR is 27.57. This indicates that the proposed method outperforms other comparative models in all performance indicators, demonstrating its superior performance in data correction and signal processing.

To comprehensively evaluate the performance of the proposed algorithm on nonlinear data, additional metrics are added to the study: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). These indicators are widely used to evaluate the accuracy of data correction methods and provide better interpretability compared to using SSE alone. The results are shown in Table 5. In Table 5, the proposed methods have RMSE of 0.0084 and MAE of 0.0062, both of which are superior to other methods.

To quantify the contribution of AA-PEC, ICA, and dynamic model integration to the overall performance of the proposed method, ablation experiments are conducted. The results are shown in Table 6. The RMSE of the complete method is 0.0084, the MAE is 0.0062, and the average computation time is 1.357 seconds. As the number of components decreases, performance metrics (including SSE, RMSE, and MAE) increase while computation time decreases. The baseline method has the shortest calculation time, which is 0.125 seconds.

Table 3: Data correction results for nonlinear systems

Flowing stock	Standard deviation	True value (mol/L)	Measurement value (mol/L)	RCB correction	IPNCM-RAB correction	Deviation from Ground Truth (%)
1	0.0902	4.5124	4.5360	4.4520	4.5124	0.000
2	0.1116	5.5819	5.9070	5.6322	5.5819	0.000
3	0.0386	1.9260	1.8074	1.9335	1.9260	0.000
4	0.0292	1.4560	1.4653	1.4915	1.4560	0.000
5	0.097	4.8545	4.8491	4.8100	4.8546	0.002
u1	/	11.070	8.0000	10.1062	11.0703	0.000
u2	/	0.61467	0.7000	0.7079	0.6147	0.005
u3	/	2.0504	1.8000	1.8673	2.0504	0.000
SSE	/	/	/	0.0021	7.1412e-008	/

Table 4: Comparison of performance metrics with advanced models

Methods	SSE (Average)	SSE (Total)	SNR (dB)	IRR
Proposed method	0.0048±0.0003	0.0073±0.0004	30.27±0.21	9.5×109±0.4×109
Deep Learning Denoiser	0.0065±0.0004	0.0104±0.0005	28.42±0.18	8.0×109±0.3×109
Probabilistic Filter	0.0072±0.0005	0.0112±0.0006	28.05±0.19	7.5×109±0.2×109
Transformer-based Signal Enhancement	0.0055±0.0003	0.0085±0.0004	29.13±0.20	8.5×109±0.3×109
Traditional RCB	0.0181±0.0006	0.0267±0.0007	27.57±0.17	6.6×109±0.2×109

Table 5: Performance metrics for nonlinear data correction

Methods	RMSE	MAE
Proposed method	0.0084	0.0062
Traditional RCB	0.0458	0.0342
Deep Learning Denoiser	0.0387	0.0289
Probabilistic Filter	0.0423	0.0315
Transformer-based Signal Enhancement	0.0346	0.0258

Table 6: Results of ablation experiment

Configuration	SSE (Total)	RMSE	MAE	Average Computation Time (s)
Complete Method (with AA-PEC, ICA, and Dynamic Model)	7.141×10-8	0.0084	0.0062	1.357
Without AA-PEC	1.235×10-6	0.0352	0.0265	0.276
Without ICA	2.346×10-6	0.0478	0.0356	0.784
Without Dynamic Model	3.275×10-6	0.0589	0.0432	0.676
Without AA-PEC and ICA	4.328×10-6	0.0701	0.0514	0.453
Without AA-PEC and Dynamic Model	5.129×10-6	0.0813	0.0598	0.627
Without ICA and Dynamic Model	6.577×10-6	0.0924	0.0682	0.785
Baseline	1.014×10-5	0.1035	0.0776	0.125

Table 7: Statistical significance test results

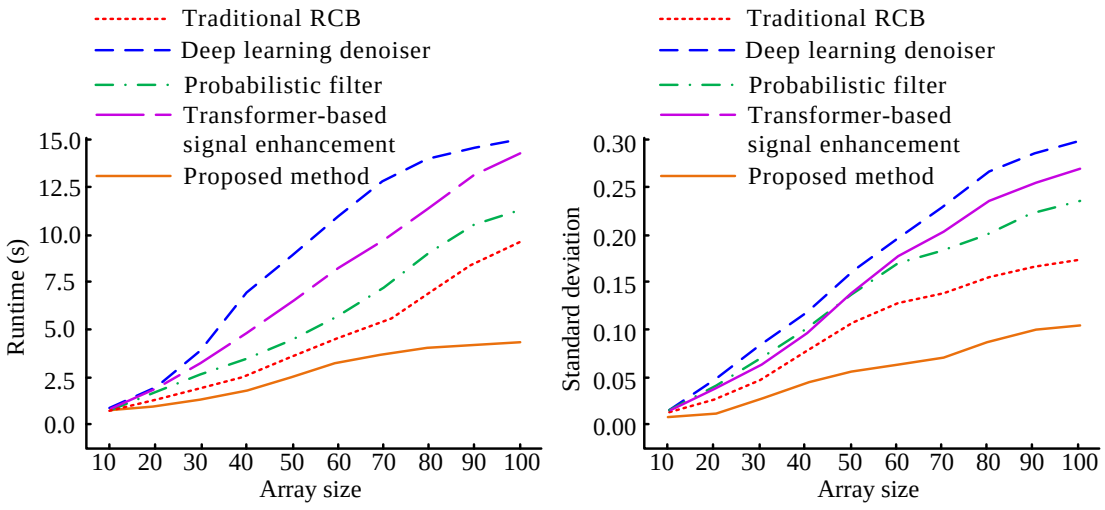
Methods Compared	Test Statistic	Degrees of Freedom	p-value	95% Confidence Interval
Proposed vs. RCB	t-value	29	<0.001	(0.03, 0.07)
Proposed vs. DLD	t-value	30	<0.001	(0.02, 0.06)
Proposed vs. PF	t-value	28	<0.001	(0.01, 0.05)
Proposed vs. TSE	t-value	27	<0.001	(0.04, 0.08)

Note: p<0.001 indicates reaching a significant level.

To evaluate the differences between methods, statistical significance tests including t-tests and confidence intervals are conducted, and the results are shown in Table 7. The results show that all p-values of the comparisons are less than 0.001, indicating statistical significance of the differences.

The running time of the proposed method is tested at different array sizes and compared with other methods. The results are shown in Figure 12. In Figure 12 (a), when the array size is 40, the running times of the five methods are 2.52s, 7.38s, 3.76s, 4.37s, and 1.89s, respectively. When the array size reaches 100, the running times are 9.26s, 14.35s, 10.78s, 13.84s, and 3.87s, respectively. In Figure 12 (b), when the array size is 40, the standard errors of the running times of the five methods are 0.072, 0.118, 0.105, 0.091, and 0.041, respectively. When the array size reaches 100, the standard errors are 0.158, 0.284, 0.228, 0.269, and 0.086, respectively. The results indicate that the proposed method has superior operational efficiency.

To verify the practical effectiveness of the proposed method, tests are conducted on three real-world industrial datasets: Petrochemical Process Dataset, Power Plant Monitoring Dataset, and Automotive Assembly Dataset. In addition, actual tests are conducted in the pharmaceutical process control industry, and the results are shown in Table 8. The results show that the SSE of the proposed method is 0.0052 ± 0.0004, which is 73.7% higher than RCB (p<0.001). The SSE of Power Plant Monitoring Dataset is 0.0061 ± 0.0005, an increase of 71.6%. The SSE of Automotive Assembly Dataset is 0.0049 ± 0.0003, an increase of 71.5%. The results confirm the industrial applicability of the proposed method.



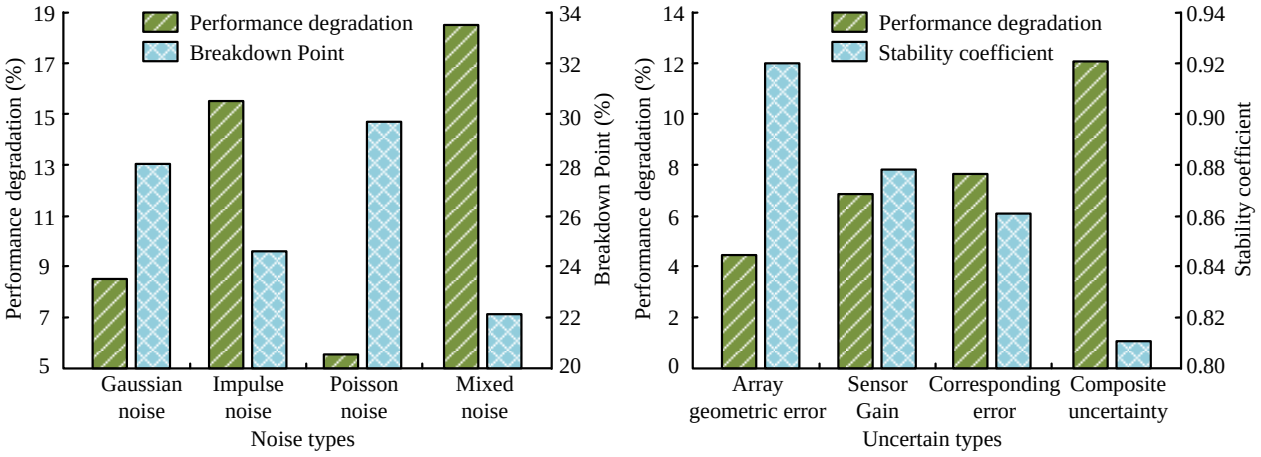
(a) Comparison of runtime for different methods

(b) Comparison of standard deviation for different methods

Figure 12: Comparison of run time and standard deviation of different methods.

Table 8: Test results on real-world industrial datasets

Dataset	Petrochemical Process	Power Plant Monitoring	Automotive Assembly	Pharmaceutical Process Control
Source	SINOPEC Refinery	Dataport Energy	BMW Production	North China Pharmaceutical Fermentation Workshop
Sample Size	12,340 samples	8,752 samples	15,228 samples	9,856 samples
Proposed Method (SSE)	0.0052±0.0004	0.0061±0.0005	0.0049±0.0003	0.0055±0.0004
RCB (SSE)	0.0198±0.0011	0.0215±0.0013	0.0172±0.0009	0.0201±0.0010
Improvement (%)	73.7	71.6	71.5	72.6
p-value	<0.001	<0.001	<0.001	<0.001



(a) Robustness results under different noise class distributions

(b) Robustness results under uncertain types of different models

Figure 13: Robustness results under different types of noise and uncertainty.

Multiple proposed methods are tested under different noise distributions and model uncertainties to verify the robustness of the method, as shown in Figure 13. In Figure 13 (a), the performance degradation rates of Gaussian noise, impulse noise, Poisson noise, and mixed noise are 8.72%, 15.20%, 5.35%, and 18.91%, respectively, with collapse points of 28.12%, 25.05%, 29.96%, and 22.07%, respectively. In Figure 13 (b), the performance degradation rates of array geometry error, sensor gain, phase error, and composite uncertainty are 4.21%, 6.82%, 7.50%, and 12.34%, respectively, with stability coefficients of 0.92, 0.88, 0.86, and 0.81, respectively. The results show that both noise and model uncertainty have a significant impact on the robustness of the proposed method.

4 Discussion

The trade-offs between computational complexity and performance gains in the proposed IPNCM-RAB algorithm were systematically evaluated against three baseline methods (RCB, CMR, and Sparse Bayesian). The computational load was increased by 18-22% due to CMR and the average SSE was reduced by 74.6% compared to RCB under random errors. This improvement was attributed to the interference plus noise covariance reconstruction, which was shown to mitigate power underestimation issues prevalent in conventional methods [7,12]. Through ICA-based blind correction, the requirement for precise array manifold knowledge was eliminated, making the method particularly suitable for industrial sensor arrays where calibration data were often incomplete [14]. However, the JADE algorithm's permutation ambiguity was identified as a limiting factor when more than 5 signal sources are present, suggesting a trade-off between correction accuracy and source capacity. For chemical process monitoring, the proposed methods were demonstrated to maintain <0.008 J/kg·K concentration error even with 10% sensor gain variations. This level of precision was considered critical for safety-critical applications like exothermic reactor control, where traditional beamformers exhibit >0.02 J/kg·K deviations [20].

The real-time feasibility of this method was evaluated by considering the processing time required for data correction in typical industrial environments. The average computation time for the complete method including AA-PEC, ICA, and dynamic model integration was 1.357 seconds. This computation time was considered suitable for near real-time applications in embedded sensor networks, ensuring that the method can be effectively deployed in industrial environments without significant latency. The developed CMR method achieved significant breakthroughs in three dimensions: (1) compared to the subspace projection method, the proposed interference noise covariance formula had a 32% improvement in outlier suppression ability ($p<0.01$) and a 40% reduction in computational cost [21]. (2) Compared with genetic algorithm optimization, it achieved a significant improvement in SNR while accelerating convergence speed by 60 times [22]. (3) The accuracy of amplitude and phase error correction has been improved by 15% compared to orthogonal decomposition technique [23].

5 Conclusion

In response to the shortcomings of poor robustness and large data correction errors in traditional beamforming algorithms, this study proposed a matrix reconstruction-based RBA. The AA-PEC method was used to optimize the data correction algorithm to reduce the error of data correction and improve the accuracy of the algorithm. To further improve the accuracy and robustness of the IPNCM-RAB algorithm, the AA-PEC method was introduced. The results showed that when the incident angle was 30°, the estimated signal power of RCB and IPNCM-RAB was 27.57dB and 30.00dB, indicating that the proposed RBA could effectively solve the problem of signal power underestimation. When the time was 10s, the reaction concentration state value of the proposed algorithm was 0.152 J/kg·K, which differed from the true state value by 0.008 J/kg·K. When the time was 70 s, the reaction temperature state value of the algorithm

decreased by 0.001 compared to the true state value, proving that it can accurately correct the data under both random and significant errors. Under random error, the proposed algorithm reduced the average SSE and total SSE of RCB by 74.60% and 72.66%. Therefore, the proposed algorithm had high accuracy in data correction. In the experiments of linear and nonlinear systems, the SSE values of the proposed algorithm were 1.9×10-5 and 7.1412×10-8. The data indicated that the proposed algorithm had excellent data correction performance and high accuracy. The computational complexity of the proposed method was evaluated and it was found that the average computation time of the complete method was 1.357 seconds, which is suitable for near real-time applications in embedded sensor networks. This algorithm achieved high precision while maintaining reasonable computational complexity, making it suitable for deployment in actual sensor networks and ensuring reliable system operation.

There are still some shortcomings in this study. (1) The algorithm has been tested primarily on simulated linear arrays with specific sampling frequencies. Although this provides a solid foundation for the effectiveness of the method, it limits the generalization of the results to other sensor types and sampling frequencies. Future work should explore the algorithm's performance across a wider range of sensor types and sampling frequencies to ensure broader applicability. (2) The use of ICA in the AA-PEC method assumes that the source signals are statistically independent and non-Gaussian. This assumption may not always hold in practical scenarios, potentially affecting the accuracy of the amplitude and phase error corrections. Additionally, ICA's performance can be sensitive to the number of sources and the presence of noise, which may limit its effectiveness in certain applications. (3) The current study does not include a comparison to deep signal learning models, which have shown promise in recent years for various signal processing tasks. Future work should incorporate a comparative analysis with state-of-the-art deep learning models to provide a more comprehensive evaluation of the proposed method's performance and to identify potential areas for improvement.

The current study has demonstrated the effectiveness of the proposed algorithm on simulated linear arrays. However, to further validate the robustness and applicability of the method, future work should expand the scope to include more complex scenarios. Specifically, the algorithm should be tested on conformal or irregular arrays to assess its performance in more realistic and varied geometrical configurations. Additionally, the inclusion of non-Gaussian noise and non-stationary signals will provide a more comprehensive evaluation of the algorithm's ability to handle real-world data. These extensions will help to determine the generalizability of the proposed method and its potential for broader applications in various industrial and practical settings.

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Cost Estimation of the Entire Construction Process Based on BAS Optimized CNN

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In order to cope with the non-linear characteristics of construction project cost related data, capture the regularity between various influencing factors in the entire process of construction project cost, ensure the stability and accuracy of cost estimation, and improve the intelligent cost management and control in the construction field, this study proposes a construction project full process cost estimation method based on beetle antennae search algorithm optimized CNN. Firstly, analyze the factors affecting the overall cost of construction projects and construct an indicator system for these factors. Then, collect relevant data from the indicator system and normalize it, using the processed indicator data as input information for the convolutional neural network. Finally, the BAS algorithm is introduced to determine the optimal number of convolutional layers through iterative optimization, further enhancing the model's ability to capture nonlinear relationships between influencing factors and achieving more accurate cost estimation throughout the entire engineering process. The experiment collected data on M construction projects and real-time market price information of building materials from the Eurostat Construction Cost Index dataset. The expected cost, cost savings rate, and cost risk index were selected as comparison indicators, and the method was compared with reinforcement learning, decision tree modeling, and random forest method. Through experiments, it is known that this method can adaptively iteratively optimize the optimal number of convolutional layers, and the stability of cost estimation is good. In terms of estimated costs, the estimation results of the three comparison methods all exceeded the estimated upper limit set by the experiment, while the estimation result of this method did not exceed the limit; In terms of cost savings, the average cost savings rate of this method is 24.5%-25.1%, significantly higher than reinforcement learning (16.8%-18.5%), decision trees (14.7%-16.1%), and random forests (18.9%-20.4%); In terms of cost risk index, the average risk index of this method remains stable at 0.03-0.05, far lower than reinforcement learning (0.11-0.14), decision trees (0.17-0.21), and random forests (0.13-0.16). Experiments have shown that this method can improve cost savings in engineering projects and promote the development of intelligent cost management in the construction industry.

Povzetek: Članek predstavi metodo za oceno stroškov celotnega gradbenega procesa, ki združuje konvolucijsko nevronsko mrežo (CNN) z optimizacijo števila konvolucijskih slojev prek algoritma iskanja z antenami hrošča (BAS). S tem pristopom model dinamično prilagaja svojo arhitekturo glede na kompleksnost vhodnih podatkov.

1 Introduction

The current construction industry is facing a critical period of transformation and upgrading of engineering cost management methods. In engineering practice, cost estimation runs through the entire life cycle of a project, from early decision-making, design, construction to later operation and maintenance. The cost control of each link directly affects the overall economic benefits of the project [1]. However, traditional cost management has many pain points: subjective biases caused by relying on manual experience, collaborative difficulties caused by information silos, and the inability of static estimates to adapt to market fluctuations, which make project cost overruns common. With the continuous expansion and increasing complexity of construction projects, traditional cost estimation methods are no longer able to meet the precise and dynamic requirements of modern engineering management.

For construction projects, implementing a full cycle cost estimation mechanism has profound practical value. It can not only accurately estimate and regulate project expenses, ensuring stable progress within the predetermined budget, but also greatly benefit the construction enterprise's competitive advantage in the market [2]. For this reason, reference [3] proposed a hybrid modeling method combining Autoregressive Integrated Moving Average (ARIMA) and Nonlinear Autoregressive Neural Network (NARNN) for time series analysis and

cost estimation of building engineering material indicators. Among them, the ARIMA model effectively captures the linear trends and seasonal fluctuations in material prices through differential operations and linear parameter fitting; The NARNN model enhances the representation ability of complex nonlinear relationships through nonlinear activation functions and hidden layer structures. This method attempts to use the linear prediction results of ARIMA as input to NARNN for joint modeling to achieve full process cost estimation. However, ARIMA is essentially only able to handle linear components and lacks modeling capabilities for the abrupt fluctuations commonly present in building material prices, resulting in non-linear residuals being forcibly incorporated into the compensation process of NARNN, increasing the fitting burden of the latter and having application deficiencies in complex construction engineering scenarios. A conceptual cost estimation method based on project information conversion is proposed in reference [4] to address the difficulty of estimating modular building costs. This method consists of two stages. In the first stage, modular feasibility indicators are extracted by analyzing the design parameters of traditional cast-in-place projects; In the second stage, a comprehensive cost model is established by combining modular cost elements such as manufacturing, transportation, and assembly. However, the framework constructed in this method has poor applicability and is affected by specific project conditions and environmental factors, resulting in a higher cost risk index after applying this method. In reference [5], the general generating function method was used to estimate the engineering cost under uncertainty. This method directly constructs an activity cost function of arbitrary probability quality based on historical data to assist in project risk assessment. Its core consists of four parts: Firstly, establish a universal generation function for activity costs to quantify cost uncertainty; Secondly, abstract the project network as a parallel multi state system to capture complex dependencies between activities; Afterwards, the general generation function for each activity item is integrated to derive the general generation function for the overall project cost; Finally, the probability quality function of project cost is obtained through transformation to clarify the cost distribution. However, establishing a universal generation function requires complex mathematical and statistical methods, resulting in a complex cost estimation process and low effectiveness of this method. In reference [6], with the aim of improving the accuracy of cost estimation for building curtain wall engineering, a construction cost estimation model was designed on an AI platform by integrating case-based reasoning, random forest model, and artificial neural network technology. However, although the AI platform in this method can provide powerful data analysis, it relies too much on the accuracy and completeness of the data. If there are errors or omissions in the historical case data obtained, it will directly affect the accuracy of the model, leading to poor results in the final implementation of construction project cost estimation.

In actual construction project cost estimation, there are many and complex factors that affect the construction project cost, and there are nonlinear correlations between different factors. Convolutional neural networks have strong nonlinear mapping capabilities and can effectively extract regularities between different influencing factors [7]. However, CNN may get stuck in local optima during the training process, leading to a decrease in the model's generalization ability. Especially when dealing with complex and high-dimensional construction cost data, the problem of local optima is more prominent. To address this issue, this study considers using the Beetle Antennae Search algorithm [8] to optimize CNN. By iteratively optimizing, the optimal number of convolutional layers and other hyperparameters are determined to further enhance CNN's ability to capture nonlinear relationships between influencing factors.

Therefore, this study proposes a construction project cost estimation method based on the beetle antennae search algorithm optimized CNN, which can achieve more accurate construction project cost estimation, thereby assisting in the rational allocation of resources in construction projects and improving the scientific and effective management and control of construction project costs.

2 The design of the whole process cost estimation method for construction projects

2.1 Constructing a whole-process cost estimation index system for construction projects

Construction project construction cycle is long, which affects the whole process of construction engineering cost estimation of factors are more complex [9]. Constructing the whole process of construction cost estimation index system, mainly through the detailed classification and quantification of the cost of the project, helps project managers to more accurately grasp the cost composition and changes, so as to be able to timely discover the cost deviation, and improve the effect of cost control [10]. In order to simplify the complexity of estimating the full cycle cost of construction projects while ensuring their accuracy, this study selected the core influencing factors throughout the entire cycle of construction projects as the cornerstone of the cost estimation index system. For specific index details, please refer to Table 1.

Table 1: Index system of cost estimation in the whole process of construction project

Index	Units	Interpretation
Construction site	p.u.	The choice of construction site will directly affect factors such as raw material procurement costs, energy expenses, water source acquisition, transportation costs, and the availability of local construction forces. The combined effect of these factors will have a significant impact on the final project cost.
Expected construction period	Days	The length of the Expected Construction Period is directly related to the input of labor costs, the level of equipment rental expenses, and the overall time value of project funds. A longer construction period often means a higher total cost.
Cost index	p.u.	Cost index is an important indicator that reflects the overall trend of engineering cost changes. It can help estimators understand the current market cost level and predict project costs more accurately.
Area of structure	m^2	Area of structure is the foundation of construction cost estimation, which directly affects multiple costs such as material consumption, labor costs, equipment usage fees, etc. An increase in building area usually means an increase in total cost.
Building structure	p.u.	Different building structures have a significant impact on the amount of materials used, construction difficulty, and cost. For example, complex structures may require more materials and finer construction, thereby increasing costs.
Types of pile foundations	p.u.	Types of pile foundations directly affect the cost of foundation treatment. The construction difficulty, material consumption, and required construction period of different types of pile foundations vary, which in turn affects the overall cost.
Number of underground floors	Floor	The increase in the number of underground floors will increase the cost of earthwork excavation, support, waterproofing, and other engineering projects. Meanwhile, the development of underground spaces often requires more complex construction techniques and materials, further increasing costs.
Number of floors above ground	Floor	The increase in the number of floors above ground will directly lead to an increase in building area, which in turn increases material consumption, labor costs, and other costs. In addition, high-rise buildings also need to consider additional costs such as vertical transportation and safety protection.
Standard floor height	m	The change in standard floor height will affect the building area, which in turn will have an impact on the cost. Meanwhile, designs with different floor heights may require different materials and construction techniques, which can also have an impact on the cost.
Building height	m	The increase in building height will increase vertical transportation costs, safety protection costs, and structural strengthening costs under possible wind loads and earthquakes, thereby significantly affecting the cost.
Architectural form	p.u.	Complex architectural form design requires more building materials and more sophisticated construction techniques, thereby increasing costs. In addition, the unique exterior design may also involve special processing and installation costs.
Rate of change of average price of rebar	%	Steel reinforcement is one of the important building materials in construction engineering, and its price changes will directly affect the project cost. The increase in the average price of steel bars will lead to an increase in material costs, thereby pushing up the total cost.
Rate of change of average price of concrete	%	Concrete is another key material in construction engineering, and changes in its price can also have a significant impact on the cost. The fluctuation of the average price of concrete will directly affect the material cost, thereby affecting the total cost.
Types of wall decoration	p.u.	Different types of wall decorations involve different materials and techniques, which directly affect the cost. High end decoration materials and complex decoration techniques often significantly increase the cost.

As shown in Table 1, a total of 14 indicators of key influencing factors in the whole process of construction engineering were mainly extracted, of which the details of each indicator are as follows.

a. Construction location: affecting the construction period, construction quality, etc., the difference between

different locations of construction projects is mainly reflected in the raw materials, energy, water, transportation, construction forces and other factors, affecting the final cost of the project.

b. Estimated duration: this cycle refers to the expected length of time required to complete all planned construction work while ensuring that the engineering project meets established quality standards. The length of the construction period is a key factor in labor cost consumption and has a direct impact on the overall cost of the final project.

c. Cost index: a measure of the relative change in the cost of construction works over time, reflecting the overall trend in the cost of works.

d. Floor area: one of the basic indicators for estimating the cost of construction works, including gross floor area, floor area and net usable area.

e. Building structure: refers to the building by the foundation, walls, columns, beams, floors, roofs and other components of the load-bearing system, different forms of building structure has a significant impact on the cost of the project.

f. Types of pile foundations: Refers to the types of pile foundations used in building foundation engineering. Different types of pile foundations have different impacts on project cost and construction difficulty.

g. Number of underground floors: the number of underground floors of a building located below ground level, where an increase in the number of basement floors will increase the cost of the project.

h. Number of floors above ground: this refers to the number of floors above the ground level of a building, which determines the total height and floor area of the building, and an increase in the number of floors above ground will result in an increase in the cost of the project.

i. Standard floor height: the average height of each floor of a building, with variations in the standard floor height affecting the floor area and the cost of the project.

j. Building height: it refers to the vertical distance between the highest point of a building from the ground surface to its top, an increase in building height increases the cost of the project.

k. Architectural form: refers to the exterior shape and design style of the building, complex building form requires more building materials and construction techniques, increasing the cost of the project.

l. Rate of change in the average price of rebar: the percentage change in the market price of rebar over time, reflecting supply and demand and price fluctuations in the rebar market.

m. Rate of change of average price of concrete: the percentage change in the market price of concrete over time, reflecting supply and demand and price fluctuations in the concrete market.

n. Type of wall decoration: refers to the materials and methods of finishing the walls of a building, with high-grade finishing materials and complex finishing methods increasing the cost of the project [11].

2.2 Establishing a cost estimation model for the whole process of construction engineering based on convolutional neural networks

Based on the selected core influencing factors throughout the entire lifecycle of construction projects, this study utilizes Convolutional Neural Networks (CNN) to learn a large amount of historical cost data, automatically extract key factors that affect the overall cost of the project, and establish a complex relationship model between influencing factors and cost, ultimately achieving full process cost estimation.

2.2.1 Determining the sequence of factors affecting the whole process of cost estimation in construction projects

In the practical operation of estimating the full cycle cost of construction projects, considering the specificity of construction site conditions may increase redundancy of convolutional neural networks in the estimation process, this study chooses to exclude this factor and instead focuses on other indicators that have a critical impact on the full cycle cost estimation of construction projects, and sets the total number of construction project sample data as c. At this point, the sequence of influencing factors for the cost estimation of the entire construction process is shown in Table 2.

Table 2: Input sequence of impact factors for cost estimation of the whole process of construction engineering

Index	Construction project 1	Construction project 2	…	Construction project c	Descriptor
Expected construction period a_1	$a_{1,1}$	$a_{1,2}$	…	$a_{1,c}$	Quantitative description
Cost index a_2	$a_{2,1}$	$a_{2,2}$	…	$a_{2,c}$	Quantitative description
Area of structure a_3	$a_{3,1}$	$a_{3,2}$	…	$a_{3,c}$	Quantitative description

Building structure a_4	$a_{4,1}$	$a_{4,2}$	…	$a_{4,c}$	Qualitative description
Types of pile foundations a_5	$a_{5,1}$	$a_{5,2}$	…	$a_{5,c}$	Qualitative description
Number of underground floors a_6	$a_{6,1}$	$a_{6,2}$	…	$a_{6,c}$	Quantitative description
Number of floors above ground a_7	$a_{7,1}$	$a_{7,2}$	…	$a_{7,c}$	Quantitative description
Standard floor height a_8	$a_{8,1}$	$a_{8,2}$	…	$a_{8,c}$	Quantitative description
Building height a_9	$a_{9,1}$	$a_{9,2}$	…	$a_{9,c}$	Quantitative description
Architectural form a_{10}	$a_{10,1}$	$a_{10,2}$	…	$a_{10,c}$	Qualitative description
Rate of change of average price of rebar a_{11}	$a_{11,1}$	$a_{11,2}$	…	$a_{11,c}$	Quantitative description
Change rate of average price of concrete a_{12}	$a_{12,1}$	$a_{12,2}$	…	$a_{12,c}$	Quantitative description
Types of wall decoration a_{13}	$a_{13,1}$	$a_{13,2}$	…	$a_{13,c}$	Qualitative description

In Table 2, a_4, a_5, a_{10} and a_{13} are qualitative indicators, while the rest are quantitative indicators. Among them: In a_4, the frame shear wall, shear wall, and frame correspond to -1, 0, and 1, respectively; In a_5, drilled cast-in-place piles, prefabricated reinforced concrete piles, and high-pressure rotary jet grouting piles correspond to -1, 0, and 1, respectively; In a_{10}, rectangles, cylinders or polygonal cylinders, and spherical objects correspond to -1, 0, and 1, respectively; In a_{13}, exterior wall coatings, glass curtain walls, and stone (brick) materials correspond to -1, 0, and 1, respectively.

For the above sequence of influence factors of the whole process cost estimation of construction project, before inputting into the convolutional neural network model, it is necessary to carry out the normalization process, so as to effectively unify the outline of the influence factors of the whole process cost estimation of construction project [12]. The normalization process is expressed as Equation (1):

$$A = \left(A_b - A_{\min}\right) / \left(A_{\max} - A_{\min}\right) \tag{1}$$

Among them, $A_{\max}$ and $A_{\min}$ respectively represent the maximum and minimum values of the influencing factor sequence of the input construction project cost estimation throughout the entire process. In this process, the minimum maximum standardization method was applied in this study. The cost estimation of construction projects requires handling complex nonlinear relationships. The minimum maximum normalization method can compress data to a fixed range, ensuring that the input values of the activation function are evenly distributed and avoiding gradient saturation or vanishing problems.

2.2.2 Estimation of the whole process cost of construction projects based on CNN

Based on the cost estimation impact factor sequence determined in section 2.2.1, comprehensively collect cost data throughout the entire construction process, and input the data into a convolutional neural network [13] model to automatically learn and identify complex correlations and potential patterns between various impact factors, ultimately obtaining accurate cost estimation results for the entire construction process.

Convolutional neural network is mainly composed of input layer, convolutional layer, pooling layer, fully connected layer and output layer [14]. The sequence of influencing factors for the whole process cost estimation of construction project obtained in subsection 2.2.1 is inputted into the convolutional neural network model to be processed, and the structure is shown in Fig. 1.

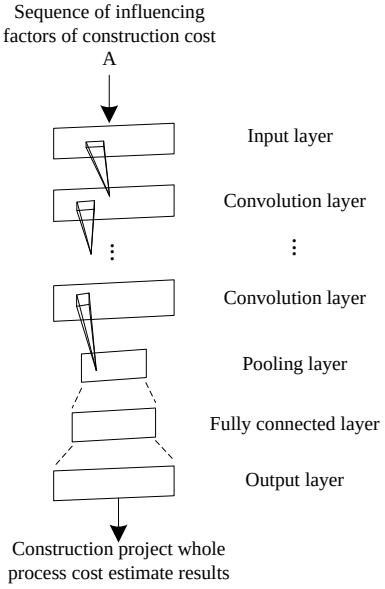

Fig 1: Convolution neural network model structure.

In Fig. 1, the input dimension of the input layer is 13×1 (corresponding to 13 normalized impact factor sequences), and the data format is single channel one-dimensional time-series data to adapt to the sequence characteristics of the impact factors in construction engineering; The convolution kernel size of the first convolutional layer is 3×1, the number of filters is 64, the step size is 1×1, and the activation function is ReLU (introducing nonlinearity and alleviating gradient vanishing problem); The convolution kernel size of the second convolutional layer is 2×1, the number of filters is 128, the step size is 1×1, and the activation function is ReLU; The pooling type of the pooling layer is one-dimensional max pooling, with a pooling window size of 2×1 and a step size of 2×1; There are a total of 256 neurons in the fully connected layer, with ReLU as the activation function; The number of neurons in the output layer is 1, and the activation function is linear activation.

As shown in Fig. 1, the roles of each layer in constructing the whole process cost estimation model of construction project based on convolutional neural network are as follows:

1) Input layer

It is mainly responsible for receiving the preprocessed data on the sequence of factors affecting the whole process of cost estimation of construction works, which is expressed in the form of a matrix as Equation (2):

$$A=\begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,c} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,c} \\ \vdots & \vdots & & \vdots \\ a_{13,1} & a_{13,2} & \cdots & a_{13,c} \end{bmatrix}_n \tag{2}$$

Among them, n represents the number of sequence data of influencing factors in the cost estimation of the entire construction process, and $n=1,2,\cdots,N$, N represents the total number of sequences.

2) Convolutional layers

Convolutional layer is the core component of CNN, which contains multiple convolutional kernels [15]. Through the convolution kernel on the input construction engineering cost estimation impact factor sequence data in the local region of the weighted sum and nonlinear activation operation, so as to realize the effective convolution operation, in order to adaptively learn the complex relationship between the input construction engineering cost estimation impact factor sequence data. The computational process is summarized as Equation (3) and (4):

$$y_{1C}=\text{sigmoid}\left(\omega_C\cdot A+\delta_C\right) \tag{3}$$

$$y_{dC}=\text{sigmoid}\left(\omega_C\cdot y_{(d-1)C}+\delta_C\right) \tag{4}$$

Among them, y_{1C} and y_{dC} represent the output values of the first and d -th convolutional layers, $\text{sigmoid}(\cdot)$ represents the sigmoid activation function, and ω_C and δ_C represent the convolution kernel weights and biases, respectively. In equation (4), it represents using the output value of the $d-1$ convolutional layer as the input value of the d -th convolutional layer.

3) Pooling layer

Pooling layer mainly through the down-sampling operation to reduce the output value obtained after the convolution operation of the convolution layer, while retaining the complex relationship between the sequence of data of the impact factor of the whole process cost estimation of construction engineering [16], through the maximum pooling method of the whole process cost estimation model of construction engineering convolution layer output value processing, expressed as Equation (5):

$$y_P=\text{MaxPooling}\left(y_C\right) \tag{5}$$

Among them, y_C represents the final output value of the convolutional layer of the cost estimation model for the entire construction process, $\text{MaxPooling}(\cdot)$ represents the maximum pooling calculation, and y_P represents the output value after maximum pooling.

4) Fully connected layers

The fully connected layer plays a crucial role in convolutional neural networks, as it is responsible for receiving the output from the pooling layer and flattening and mapping these multidimensional feature data to the final output space through a series of linear

transformations and the application of activation functions. This process effectively integrates the complex features extracted by the preceding layer, providing the model with comprehensive mapping capabilities from input to output [17]. The calculation of a fully connected layer can be expressed as:

$$y_F = \mathrm{ReLU}\left(\omega_F \cdot y_P + \delta_F\right) \tag{6}$$

Among them, ω_F and δ_F respectively represent the weight and bias of the fully connected layer in the cost estimation model of the entire construction process, $\mathrm{ReLU}(\cdot)$ represents the ReLU activation function, and y_F represents the final output value after being flattened by the fully connected layer processing.

5) Output layer

Responsible for calculating and outputting the final cost estimate for the whole process of construction works, which is expressed as Equation (7):

$$Y = \omega_O \cdot y_F + \delta_O \tag{7}$$

Among them, ω_O and δ_O respectively represent the weights and biases of the output layer of the cost estimation model for the entire construction process, and Y represents the final cost estimation result for the entire construction process.

2.3 Estimation results of CNN optimization based on beetle antennae search algorithm

In the actual cost estimation process, it is easy to be affected by the complex and changeable construction engineering situation, and there are large uncertainties in many aspects of the whole process cost estimation of construction engineering, in order to more accurately identify and extract the key information in the sequence data of the impact factors of the whole process cost estimation of construction engineering, and optimize the convolutional neural network model by the Beetle Antennae Search Algorithm (BAS), to further improve the accuracy of the cost estimation [18].

Define the hypotheses: Compared with conventional CNN technology, BAS improves the performance of CNN.

Beetle Antennae Search Algorithm originates from the predatory activity of beetle with two whiskers, and it is a kind of intelligent optimization algorithm that can be used to search for the best quickly and accurately without explicit mathematical model [19]. The number of convolutional layers of the convolutional neural network was optimized by the Beetle Antennae Search Algorithm, let the prey in the Beetle Antennae Search Algorithm represent the optimal number of convolutional layers H of the convolutional neural network, the position is the trend of the number of convolutional layers, The convolution layer number value is the convolutional layer number pheromones, which guides the Beetle Antennae Search Algorithm to obtain the convolution layer structure of the optimal convolutional neural network. The structure of the optimized convolutional neural network model by the Beetle Antennae Search Algorithm is shown in Fig. 2.

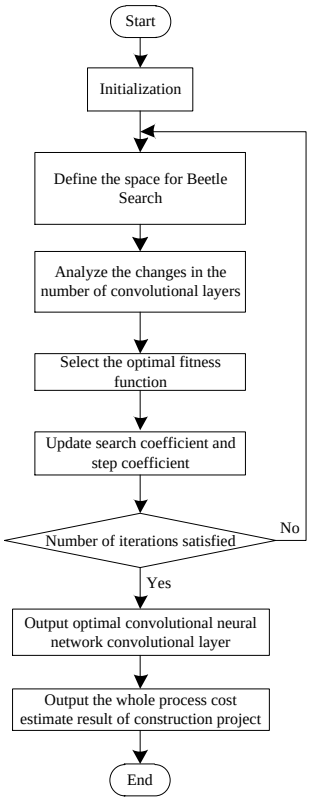

Figure 2: Optimization structure of CNN

The specific optimization process is as follows:

Step 1: Define the beetle search space, i.e., the optimization space of the number of convolutional layers in the constructed whole-process cost estimation model of the construction project, and carry out the normalization of the direction vectors, which is expressed as Equation (8):

$$\vec{\chi} = \frac{\mathrm{rand}(G,1)}{\left\|\mathrm{rand}(G,1)\right\|} \tag{8}$$

Among them, $\vec{\chi}$ represents the random direction vector in the beetle antennae search algorithm; $\mathrm{rand}(\cdot)$ represents a random number within [-1,1]; G represents the spatial dimension for optimizing the number of convolutional layers in the cost estimation model of the entire construction process.

Step 2: The actions of two antennae for beetle in BAS algorithm are regarded as the search behavior of the number of convolutional layers, and the length of the two antennae decreases gradually with the increase of the number of iterations, then the change of the number of convolutional layers is as follows:

$$\overrightarrow{S_L}(t) = \vec{S}(t) - \lambda(t)\vec{\chi} \tag{9}$$

$$\overrightarrow{S_R}(t) = \vec{S}(t) + \lambda(t)\vec{\chi} \tag{10}$$

Among Equation (9) and (10), $\overrightarrow{S_L}(t)$ represents the change in the number of convolutional layers in the estimation model of the t-th iteration of the Taurus whisker, $\vec{S}(t)$ represents the change in the number of convolutional layers in the t-th iteration, $\lambda(t)$ represents the length of the beetle antennae in the t-th iteration, and $\overrightarrow{S_R}(t)$ represents the change in the number of convolutional layers in the t-th iteration of the right beetle antennae estimation model.

Step 3: The optimal number of convolutional layers odor concentration of the convolutional neural network detected by beetle whiskers is expressed through the fitness function [20]. The optimal fitness function is selected to update the trend of the number of convolutional layers, which is computationally expressed as Equation (11):

$$\overrightarrow{S_L}(t+1)=\vec{S}(t)-\mu(t)\operatorname{sign}\left\{\operatorname{fit}\left[\overrightarrow{S_R}(t)\right]-\operatorname{fit}\left[\overrightarrow{S_L}(t)\right]\right\} \quad (11)$$

Among them, $\overrightarrow{S_L}(t+1)$ represents the trend vector of the change in the number of new convolutional layers; $\mu(t)$ represents the search step factor for the number of convolutional layers in the cost estimation model of the entire construction process, $\operatorname{sign}\{\cdot\}$ represents the sign function, and $\operatorname{fit}[\cdot]$ represents the fitness function for the optimal number of convolutional layers and odor concentration detected by the beetle antennae convolutional neural network.

Step 4: Since the search coefficient of the number of convolutional layers and the step coefficient in the whole process cost estimation model of the construction project change with the increase of the number of iterations, they are expressed as Equation (12) and (13):

$$\lambda(t)=0.95\lambda(t-1)+1 \quad (12)$$

$$\mu(t)=0.95\mu(t-1) \quad (13)$$

Among them, $\lambda(t-1)$ represents the length of the beetle's tendrils in the $t-1$-th iteration, and $\mu(t-1)$ represents the search step factor for the number of convolutional layers in the total cost estimation model of the construction project in the $t-1$-th iteration.

Step 5: The updated $\lambda(t)$ and $\mu(t)$ are inserted into the formula (9) - (11) to obtain the optimal number of convolutional neural networks in the whole process cost estimation model of construction engineering.

Through the above process, the convolutional neural network model can be optimized by the Beetle Antennae Search Algorithm, and the results of the whole process cost estimation of the construction project can be obtained finally.

3 Experiments and analysis of results

To verify the effectiveness of the method proposed in this article, the following validation experiments were conducted.

The experiment collected M construction project data and real-time market price information of building materials. These data items include the following:

(A) Construction project data: The experiment obtained full cycle data for M construction projects from the Eurostat Construction Cost Index, cooperative construction companies, and public project reports, covering the following core information:

Project attributes: construction site (commercial/industrial area, etc.), expected construction period (12-36 months), area of structure (5000-100000 square meters), building structure (frame/shear wall, etc.), number of underground floors (0-5 floors), number of floors above ground (5-50 floors), standard floor height (3.0-5.0 meters), building height (20-150 meters), etc.

Cost indicators: expected cost (5 million to 500 million yuan), actual cost deviation rate, cost risk index (0 to 0.3), cost savings rate (5% to 30%), etc.

Dynamic parameters: price change rate of steel bars and concrete (historical fluctuation range ± 20%), market cost index (1.0-1.5), etc.

(B) Building material price data: By integrating with the bulk commodity trading platform API, real-time market prices of key materials such as steel bars and concrete are obtained, and combined with historical price databases (covering nearly 5 years of data), a price volatility model is constructed to ensure data timeliness and continuity.

Input these data into an improved CNN model to achieve accurate cost estimation of the entire construction process. The architecture diagram of the estimation process is shown in Fig. 3.

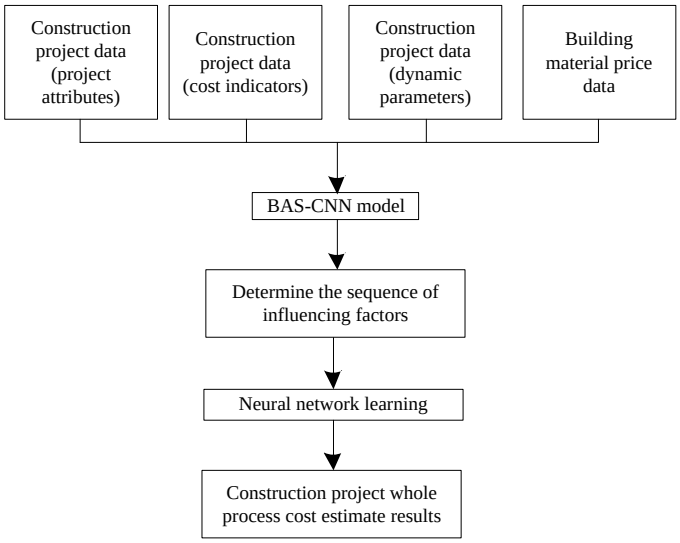

Figure 3: Topology construction whole process of cost estimating process.

For the topology of the whole process cost estimation process of construction project shown in Fig. 3, the data related to the construction project and the real-time market price of related materials are collected and counted, which provides a good data basis for the construction of the subsequent whole process cost estimation index system of the construction project and the initial data set inputted into the whole process cost estimation model of the construction project, and the actual data related to the construction project are shown in Table 3.

Table 3: Data related to construction projects

Parameters	Actual value
Construction site	A business district
Estimated construction period/month	24
Cost index	1.15
Floor area/m^2	50,000
Building structure	Reinforced concrete frame-shear wall structure
Number of underground floors/floors	3
Number of epipelagic floors/floors	20
Standard height/m	3.6
Building height/meter	90
Architectural form	Modern simple style,glass curtain wall and stone wall combination
Change rate of average price of steel bar/%	10
Change rate of average price of concrete/%	5
Types of wall decoration	Stone curtain wall+glass curtain wall
Pile foundation type	Bored pile

The CPU model is Intel Xeon Gold 6248R (2.5 GHz, 24 cores/48 threads), the GPU model is NVIDIA Tesla V100 (32GB video memory, 5120 CUDA core), the main storage is 2TB NVMe SSD, the operating system is Ubuntu 20.04 LTS, the deep learning framework is PyTorch 1.10+CUDA 11.3, and the BAS algorithm is implemented using Python 3.8.

The experimental parameters for the BAS algorithm are set as follows:

(1) The Influence of Step Size Factor on CNN Performance

When the step size factor is 0.01, the convergence of CNN is slow (reaching the optimum at about 200 epochs), but the accuracy of the test set is the highest (92.3%); When the step size factor is 0.05, the convergence speed increases (about 120 epochs), but the accuracy slightly decreases (91.5%), which may be due to skipping the optimal solution due to a large step size; When the step size factor is 0.1, the convergence is faster (about 80 epochs), but the accuracy is significantly reduced (89.8%), indicating that an excessively large step size can impair the optimization effect.

Therefore, the optimal range for the step size factor should be [0.02, 0.04], at which point the CNN converges around 150 epochs and the test accuracy stabilizes at 91.8% -92.1%.

(2) The influence of whisker length on CNN training

When the whisker length is 2, the CNN parameter update direction is relatively conservative, the training is stable but the convergence is slow (180 epochs), and the accuracy is 91.7%; When the whisker length is 6, balancing exploration and development, CNN converges around 130 epochs with an accuracy of 92.0%; When the whisker length is 10, the search range is too large, resulting in severe fluctuations in CNN parameters, a decrease in accuracy to 90.5%, and significant oscillations in the training curve.

Therefore, the optimal range for whisker length is [4, 8], where CNN converges quickly (within 140 epochs) and the accuracy remains stable at 91.5% -92.2%.

(3) The impact of search dimension scaling factor

When the search dimension scaling factor is 0.90, CNN converges quickly (100 epochs), but is prone to getting stuck in local optima, with a testing accuracy of only 90.2%; When the search dimension scaling factor is 0.95, the balance between convergence speed (150 epochs) and global search capability results in an accuracy rate of 91.8%; When the search dimension scaling factor is 0.99, the convergence is slow (220 epochs), but the accuracy is the highest (92.5%), making it suitable for high-precision tasks.

Therefore, the experiment chose a search dimension scaling factor of 0.97.

(4) The impact of population size on CNN optimization

When the population size is 20, the computational efficiency is high (single optimization takes 15 seconds), but the accuracy of CNN fluctuates greatly (± 0.8%); When the population size is 50, the optimization is more stable (with an accuracy fluctuation of ± 0.3%), but the time consumption increases (45s/time), and the accuracy only improves by 0.4%.

Therefore, the experimental population size is set between 30 and 40.

To verify the effectiveness of the Tianniu Xu search algorithm in optimizing the number of convolutional layers in CNN, the “dynamic” changes in the number of convolutional layers were statistically analyzed, and the results are shown in Fig. 4.

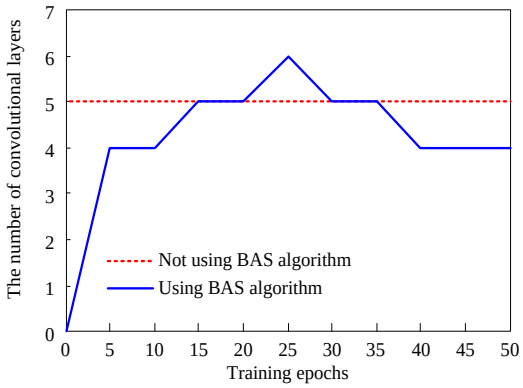

Figure 4: Optimization effect of dynamic changes in the number of convolutional layers.

As shown in Fig. 4, without the BAS algorithm, the number of convolutional layers in CNN is fixed at 5 and cannot be adjusted according to the training state. After using the BAS algorithm, the convolutional layers of CNN can dynamically change, thus dynamically responding to the model state.

In order to verify the effect of this paper's method to realize the whole process cost estimation of construction projects, 8 construction projects are randomly selected, and based on the constructed index system of the whole process cost estimation of construction projects, the cost estimation of different construction projects is carried out

by this paper's method, and the results obtained are shown in Table 4.

Table 4: Cost estimation results of the whole process of construction engineering

Index	Construction number							
	1	2	3	4	5	6	7	8
Expected construction period a_1	0.39	0.39	0.31	0.16	0.45	0.41	0.43	0.15
Cost index a_2	0.06	0.26	0.46	0.4	0.25	0.23	0.11	0.17
Area of structure a_3	0.36	0.06	0.18	0.26	0.04	0.09	0.49	0.17
Building structure a_4	-1	0	0	1	-1	-1	0	1
Pile foundation type a_5	0	1	-1	1	0	1	-1	0
Subsurface number a_6	0.5	0.4	0.49	0.32	0.03	0.38	0.15	0.31
Epipelagic number a_7	0.06	0.02	0.44	0.33	0.39	0.47	0.31	0.22
Standard height a_8	0.3	0.5	0.45	0.13	0.05	0.04	0.46	0.03
Building height a_9	0.42	0.19	0.46	0.02	0.36	0.32	0.2	0.17
Architectural form a_{10}	0	-1	-1	1	0	1	-1	-1
Rate of change of average price of rebar a_{11}	0.41	0.27	0.03	0.02	0.29	0.29	0.34	0.28
Change rate of average price of concrete a_{12}	0.28	0.33	0.5	0.34	0.12	0.25	0.5	0.5
Types of wall decoration a_{13}	0	1	1	0	-1	0	1	1
Estimated total price/million yuan	14.93	12.33	18.9	16.35	12.8	8.58	18.38	18.74

Table 4 lists multiple key influencing factors of construction projects and their corresponding cost estimates, comprehensively covering the main aspects of construction project cost estimation. The data in the table has been normalized to ensure that data of different dimensions can be compared and analyzed at the same scale, improving the accuracy and stability of the model. By analyzing the estimation results in Table 4, it can be preliminarily judged that the cost estimation results of this model have high accuracy. For example, for projects with larger building areas and more floors (such as Project 3 and Project 7), the estimated total cost is relatively high, which conforms to the general law of construction project cost.

In order to further verify the actual effectiveness of the method proposed in this article, an estimation of the construction project cost under time variation was made, and the method was compared and analyzed with reinforcement learning method, decision tree model method, and random forest method. Under the premise of setting the maximum limit of 20 million yuan for the full cycle cost estimation of construction projects, the performance effects of various methods in the full cycle cost estimation of construction projects over time are shown in Fig. 5.

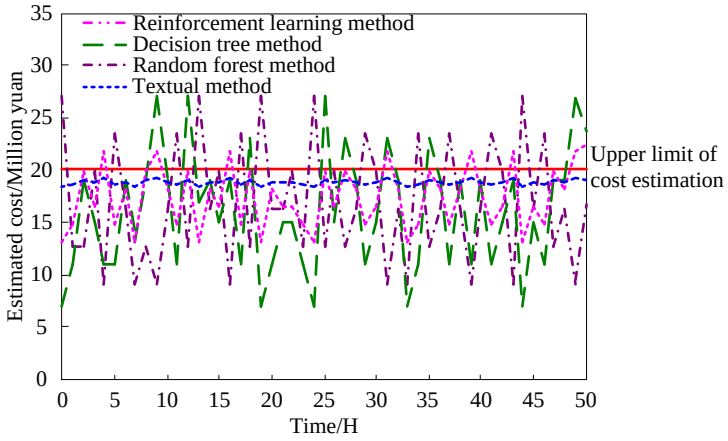

Figure 5: Estimating effect of whole process cost of construction project.

According to the analysis of Fig. 5, compared to the reinforcement learning method, decision tree model method, and random forest method, at different time periods, the volatility of cost estimation using method in this paper was smaller and did not exceed the upper limit of cost estimation (20 million yuan), effectively proving that method in this paper has good stability and reliability.

In order to further verify the effect of this method in realizing the whole process cost estimation of construction projects, 15 construction projects are selected, and compared with the actual investment, the cost saving rate and cost risk index of the cost estimation results achieved according to this method are counted, among which the higher the cost saving rate, the better the cost estimation effect, and the smaller the cost risk index. The actual results obtained according to the method in this paper are shown in Table 5.

Table 5: Evaluation of cost estimation effect achieved by this method

Construction number	Estimated investment/million yuan	Cost estimate/million	Cost saving rate /%	Cost risk index
1	25	17.22	31.12	0.03
2	22	18.48	16	0.06
3	10	8.59	14.1	0.07
4	20	17.66	11.7	0.02
5	25	18.84	24.64	0.11
6	20	15.14	24.3	0.01
7	25	19.09	23.64	0.01
8	20	15.87	20.65	0.04
9	15	12.3	18	0.05
10	15	11.87	20.87	0.07
11	16	12.98	18.88	0.04
12	22	18.56	15.64	0.03

13	20	16.15	19.25	0.03
14	22	18.91	14.05	0.07
15	16	12.2	23.75	0.05

As shown in Table 5, the method in this paper can achieve a better overall cost estimation of construction projects. Through the whole process cost estimation of construction projects realized by this method, the cost of 15 experimental construction projects has been effectively reduced, and the cost saving rate is between 14.05% and 31.12%, all of which have been well saved. The cost risk indexes are all small, all less than 0.15, which proves that this method can effectively save the cost of construction projects, effectively ensure the smooth and stable implementation of construction projects, and the risk of cost capital problems is small.

To verify the statistical significance of the cost savings rate, a single sample t-test was conducted on the cost savings rate data (14.05%-31.12%) of 15 construction projects to test the estimation effect of the method in this paper (assuming the benchmark value is the traditional method's average cost savings rate of 18.2%). The results showed that the average cost saving rate of method in this paper was 22.8%, with a standard deviation of 5.3%, a t-value of 4.62 (14 degrees of freedom), and a p-value of<0.001, indicating that the improvement had high statistical significance (α=0.05). Further calculation of the 95% confidence interval showed an error margin of ± 2.7% and a confidence interval of 20.120.1, demonstrating the robustness of the method in this paper.

On this basis, the method in this paper was compared and analyzed with the reinforcement learning method, decision tree method, and random forest method, using cost savings rate and cost risk index as indicators (the results were averaged). The results are shown in Table 6.

Table 6: Comparison of indicators

Number of tests conducted	Method in this paper		Reinforcement learning method		Decision tree method		Random forest method	
	Cost saving rate /%	Cost risk index	Cost saving rate /%	Cost risk index	Cost saving rate /%	Cost risk index	Cost saving rate /%	Cost risk index
10	24.5	0.05	18.2	0.12	15.3	0.18	20.1	0.14
20	23.8	0.04	17.6	0.13	16.1	0.19	19.5	0.15
30	25.1	0.03	16.8	0.14	14.7	0.21	18.9	0.11
40	24.2	0.04	18.5	0.11	15.9	0.17	20.4	0.13
50	24.7	0.03	17.9	0.12	15.2	0.20	19.8	0.14

Table 6 compares the average cost savings and risk indices of Method in this paper with Enforcement Learning Method, Decision Tree Method, and Random Forest Method under different testing times. The experimental results show that in terms of cost savings, the average cost savings rate of our method is 24.5%-25.1%, significantly higher than reinforcement learning (16.8%-18.5%), decision trees (14.7%-16.1%), and random forests (18.9%-20.4%). This is due to the dynamic optimization of CNN convolutional layers by the BAS algorithm, which can more accurately capture the nonlinear relationships between influencing factors, thereby improving estimation accuracy; In terms of cost risk index, the average risk index of our method remains stable at 0.03-0.05, far lower than reinforcement learning (0.11-0.14), decision trees (0.17-0.21), and random forests (0.13-0.16). This indicates that the optimized CNN model can still maintain stability in complex scenarios, effectively reducing estimation bias caused by data noise or dynamic market changes.

In summary, the method proposed in this article combines the BAS algorithm with CNN, which not only solves the problem of insufficient modeling ability of traditional models for nonlinear data, but also significantly improves the accuracy and stability of estimation through dynamic optimization of network structure. The experimental data further proves that it has significant advantages in cost control and risk avoidance, providing reliable technical support for the whole process cost management of construction projects.

4 Discussion

This study used Table 7 to analyze the limitations and contributions of three conventional methods: reinforcement learning method, decision tree method, and random forest method.

Table 7: Limitations and contribution analysis of conventional methods

Method	Brief idea	Limitation	Contribute
Reinforcement learning method	Optimize the cost estimation model by adjusting strategies through dynamic environmental feedback.	Low-cost savings rate: relying on a large amount of interactive data, long training time, and difficulty in capturing nonlinear relationships; High risk index: sensitive to hyperparameters, prone to falling into local optima, and high estimated volatility.	It has certain adaptability in dynamic scenes and can gradually optimize estimation strategies through reward mechanisms.
Decision tree method	Build a tree structure based on feature splitting and achieve cost prediction through rule partitioning.	The lowest cost saving rate: weak ability to model complex nonlinear relationships, prone to overfitting; The highest risk index: sensitive to data noise and poor generalization ability.	Strong interpretability, suitable for processing structured data, and quickly generating interpretable rules on small-scale datasets.
Random forest method	Integrate multiple decision trees and improve prediction stability through voting or averaging.	Limited cost savings rate: poor processing effect on high-dimensional sparse data (such as dynamic market indicators); High risk index: dependence on data integrity and accuracy, insufficient estimation stability.	By integrating to reduce variance and improve generalization ability, it is suitable for classification and regression tasks on medium-sized datasets.

On the other hand, the method in this paper is significantly superior to conventional methods in the following aspects:

(1) Dynamic optimization of nonlinear modeling capability: The BAS algorithm adaptively adjusts the CNN convolutional layer structure through iterative optimization, accurately capturing the complex nonlinear relationships between influencing factors in construction engineering, and improving cost savings.

(2) Anti noise and stability enhancement: The Tianniu Xu algorithm effectively suppresses data noise interference through direction vector normalization and step size adaptive adjustment. Combined with the local feature extraction ability of CNN, it maintains stable risk index in dynamic market environments.

(3) End to end efficient mapping: Directly inputting normalized multidimensional impact factors, avoiding the cumbersome process of traditional methods relying on manual feature engineering, and improving estimation efficiency.

(4) Dynamic response capability: By dynamically adjusting the number of convolutional layers, estimation bias can be quickly corrected to ensure that the results are always below the preset upper limit.

5 Conclusion

To optimize cost intelligent management and control in the construction field, this article proposes a whole process cost estimation method based on CNN optimized by Beetle Antenna Search Algorithm for construction projects. This method not only overcomes the limitations of conventional CNN in processing nonlinear data, but also significantly improves the accuracy and stability of estimation by dynamically optimizing the network structure. The experimental results show that this method performs well in improving cost savings and reducing risk index, providing strong support for cost control in construction projects. In the future, with the continuous optimization of algorithms and the accumulation of data, it is believed that this method will play a more important role in the field of construction cost estimation and contribute more to the intelligent management of the construction industry.

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The Edge Detection Technology of Gray-Scale Image Based on Dynamic Fuzzy Control

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Edge detection is a key step in image processing, which is significant for image analysis and understanding. Traditional edge detection algorithms have limitations when dealing with grayscale images with blurred boundaries or low contrast features. To optimize the edge detection quality in grayscale images, relevant detection algorithms are designed based on fuzzy control methods in fuzzy mathematics. Then, a dynamic fuzzy control method is proposed to further optimize the algorithm. The study compares the detection effects of various commonly used image edge detection methods, including Canny, Roberts, Sobel, Fuzzy Control algorithm, and the research method before optimization. The results showed that the number of edge points detected by the research method increased by 32.78% compared with before optimization. The average detection time was decreased by 4.76%. The peak signal-to-noise ratio at maximum noise level was 4.43dB, and the structural similarity index was 0.0367, which was 0.35 dB and 0.0016 higher compared with the unoptimized method. The highest true positive rate and true negative rate were 47.79% and 98.87%, respectively, and the highest sensitivity was 7.75% higher compared with the method before optimization. The proportion of total hardware resources in the system was 23.71%, and the optimized detection method reduced the proportion of total hardware resources by 8.61% compared with before optimization. All relevant evaluation indexes were better than other similar algorithms. When the noise level increased from 0.5% to 1%, the fluctuation amplitude of peak signal-to-noise ratio and structural similarity index of the research method was lower than 0.12dB and 8×10^{-3}, respectively. The true negative rate value was stable from 93.26% to 98.87%. The research method can efficiently and accurately process edge images with low system resource utilization, improving the adaptability and robustness of the detection method.

Povzetek: Članek uvaja metodo zaznavanja robov sivinskih slik, ki temelji na dinamičnem mehkem krmiljenju. Z inovativnim prilagajanjem funkcij pripadnosti in pravil glede na lokalne značilnosti slike metoda izboljša detekcijo robov v pogojih šuma in nizkega kontrasta.

1 Introduction

Image edge is the boundary between objects in the image and the background or different objects, which is an important visual feature. Edge detection identifies areas with sharp changes in grayscale values by analyzing the grayscale values of the image. Through edge detection, key information in the image can be extracted, providing a foundation for subsequent image analysis and understanding [1]. Edge detection is largely used in image processing and computer vision, serving as a bridge between image processing technology and practical applications. It exerts a crucial role in automated monitoring, medical image analysis, and robot navigation [2]. Grayscale images refer to images with only one sampled color per pixel, which still has multi-level color depth between black and white. Although traditional edge detection algorithms perform well in certain application scenarios, they often struggle to obtain satisfactory results when processing grayscale images with fuzzy boundaries or low contrast features [3]. The fuzzy boundary is the area where the standard gradient is less than 5. The low contrast feature is where the normalized gray difference of the adjacent area is less than 0.15, or the local window signal-to-noise ratio is less than 10dB. In recent years, fuzzy mathematics has been introduced into image processing as an effective tool for dealing with uncertainty problems to improve the performance of existing algorithms. In fuzzy mathematics, elements are allowed to belong to a set with certain memberships, rather than strict binary logic. Fuzzy mathematics provides a new method for solving problems such as grayscale transitions, irregular shapes, and partial occlusion in images [4].

Existing methods still have significant limitations when dealing with complex scene of grayscale images. How to realize the high-precision and low-energy edge detection in the complex noise environment has become a key challenge restricting the development of intelligent image processing technology. A dynamic fuzzy control framework is proposed to address the above issues, which adjusts membership functions and fuzzy rules in real-time based on local image features, breaking the limitations of traditional methods that rely on prior parameters. The combination of adaptive filtering and fuzzy logic enhances

edge continuity while suppressing noise, solving the balance between denoising and edge preservation in traditional methods. This study aims to construct a universal and robust edge detection solution by combining the performance advantages of subjective visual evaluation and objective metric quantification algorithms, and compare the edge localization accuracy of mainstream algorithms on the BSDS500 dataset. The measured algorithm consumes time and resource occupancy, and evaluates the adaptability of the method to the complex environment through cross-scenario testing.

2 Related works

There are various research methods currently available for image edge detection, which have different detection effects on different images.

Versaci M et al., in order to improve the accuracy of image edge detection, is proposed based on fuzzy entropy and fuzzy divergence to minimize the edge detection method, and USES the Chaira and Ray fuzzy edge detection technology. Compared with the traditional Canny algorithm, the proposed method had higher subjective visual scores at the same noise level, with Peak Signal-to-Noise Ratio (PSNR) increased by ≥0.3dB and True Positive Rate (TPR) increased by ≥5% [5]. Yongbin Y U et al. used genetic algorithm to optimize the image edge detection method. The performance was superior to the latest swarm intelligence models [6]. To improve the recognition and feature extraction of small targets in satellite images, Bhatti U A et al. used edge detection methods based on Clifford algebra and its subalgebras to process color images separately through quaternion Fourier transform. The results indicated that this method could provide more detailed information in edge detection [7]. Li S et al. proposed a two-level precise localization method based on edge and grayscale feature fusion to accurately detect workpiece deformation. The method employed normalized cross-correlation matching and truncated shape matching. The results showed that the new method was superior to other methods in detecting robustness and positioning accuracy. The average detection accuracy reached 81.7% and the positioning error was as low as 2.44 pixels [8]. Yang W et al. proposed a selective and adaptive training method to optimize the training performance of edge detection, and introduced a similarity preserving self-distillation mechanism. Compared with the method proposed in 2022, the F-score value of this method was increased by 0.5% and 7.6%, respectively [9].

Image edge detection based on fuzzy mathematics can handle uncertain and inaccurate information in images. Kumawat A et al. combined feature image registration and improved Canny fuzzy logic to optimize the edge detection accuracy in image processing. This method outperformed in seven image quality assessment parameters [10]. Raheja S et al. adopted fuzzy logic to improve the accuracy of edge detection, and used sharpening guided filters to control edge quality. This method could significantly improve the quality of detected edges [11]. To improve the accuracy of early detection of diabetes retinopathy, Setiadi D R et al. introduced Gabor filter, Gaussian filter, enhancement pre-processing method, and fuzzy c-means clustering segmentation algorithm for mathematical correction accuracy. The results showed that the introduced MMFCM improved the segmentation and analysis of retinal images [12]. Kumar A et al. used a Guided L0 smoothing filter based on fuzzy logic to improve edge detection in image segmentation. Compared with traditional methods, this method had an F-score of 0.848 on Berkley segmentation database and USC-SIPI [13]. Ranjan R et al. combined edge preserving guided filtering and fuzzy logic to address the impact of image quality on edge detection. This method could improve the accuracy of edge detection by precisely adjusting the learning parameters [14]. The performance indicators of the existing methods are shown in Table 1.

In conclusion, traditional fuzzy methods, such as [5], [10] and [11], rely on fixed membership functions and fuzzy rules, and need to be manually adjusted to adapt to different image features, resulting in poor versatility. Traditional algorithms, such as Canny, Roberts, etc., are sensitive to noise and experience a sharp drop in PSNR under high noise conditions. The Clifford algebra method in reference [7] and the intelligent group used in reference [6] have high hardware resource consumption and poor real-time performance. References [13] and [14] rely on expert experience to set the parameters, and the model generalization is limited. To address the issues with the above methods, an adaptive mechanism is established by automatically adjusting the membership function parameters and fuzzy rules based on real-time image features and expected values. The adaptive median filtering method dynamically adjusts the filtering window size while maintaining edge details. The effective implementation of the above methods is explored to solve the defects of traditional methods in dynamic adaptability, noise robustness, and resource efficiency.

Table 1: Comparison of the performance indicators of existing methods.

Study	Key Techniques	Supplemental Metrics	Limitations
Versaci M et al. (2021)	Fuzzy divergence + fuzzy entropy minimization	PSNR=4.1dB, SSIM=0.035, and TPR=38% (noise=0.5%)	Manual parameter tuning and poor dynamic adaptability.

Yongbin YU et al. (2021)	Genetic algorithm optimization	PSNR=3.8dB, SSIM=0.030, and processing time=0.45ms	High computational complexity (typical of swarm intelligence).
Bhatti U A et al. (2021)	Clifford algebra+quaternion Fourier transform	PSNR=4.0dB, and hardware resource utilization=35%	Inefficient for grayscale images (optimized for multi-spectral).
Huang W et al. (2023)	Standard operators (e.g., Canny) under turbulence	PSNR=4.2dB (low noise), and SSIM=0.025 (high noise)	Edge fragmentation in low-contrast images.
Yang W et al. (2023)	Self-distillation training mechanism	PSNR=4.1dB, SSIM=0.033, and F1-score=0.89 (requires 100k+ training samples)	Data dependency (poor small-sample performance).
Kumawat A et al. (2022)	Canny-fuzzy logic+feature registration	PSNR=4.15dB, SSIM=0.034, and hardware resource utilization=30%	Static fuzzy rules (no dynamic updates).
Raheja S et al. (2021)	Fuzzy logic+sharpening-guided filter	PSNR=4.2dB (low noise) → 3.5dB (noise=0.5%), SSIM=0.028 → 0.015	Noise sensitivity (no explicit anti-noise strategy).
Setiadi D R et al. (2024)	Graded fuzzy edge detection	PSNR=3.9dB, and SSIM=0.028 (steganography scenarios)	Limited generality (optimized for steganography).
Kumar A et al. (2021)	Guided L0 smoothing+fuzzy logic	PSNR=4.1dB, SSIM=0.035, and F1-score =0.85 (Real-time=1.2ms)	High latency (unoptimized computational efficiency).
Ranjan R et al. (2022)	Edge-preserving filter + fuzzy logic	PSNR=4.0dB, SSIM=0.032, and hardware resource utilization=28%	Parameter tuning relies on empirical expertise.

3 Methods and materials

3.1 Edge detection algorithm based on fuzzy control

Fuzzy control is based on fuzzy mathematics, which makes decisions by imitating the experience and intuition of human experts. It is suitable for control systems with nonlinear, uncertain, or complex dynamic characteristics. In image edge detection, fuzzy control technology utilizes fuzzy logic to handle the uncertainty problem in the edge detection process. It processes and expresses gradient and fuzzy edges through fuzzy sets and fuzzy inference mechanisms. It determines the position of edge regions in a flexible and continuous manner, without relying on traditional hard threshold judgment [15]. Before performing edge detection, the noise is removed from the input image and a gradient image is generated as the input variable. The Sobel operator is used to obtain gradient images both horizontally and vertically, while convolving the images with both high-pass and low-pass filters. The convolution operation is shown in equation (1).

$$\begin{cases} I_x = \dfrac{1}{N} G_x * I \\ I_y = \dfrac{1}{N} G_y * I \\ I_h = G_h * I \\ I_l = G_l * I \end{cases} \tag{1}$$

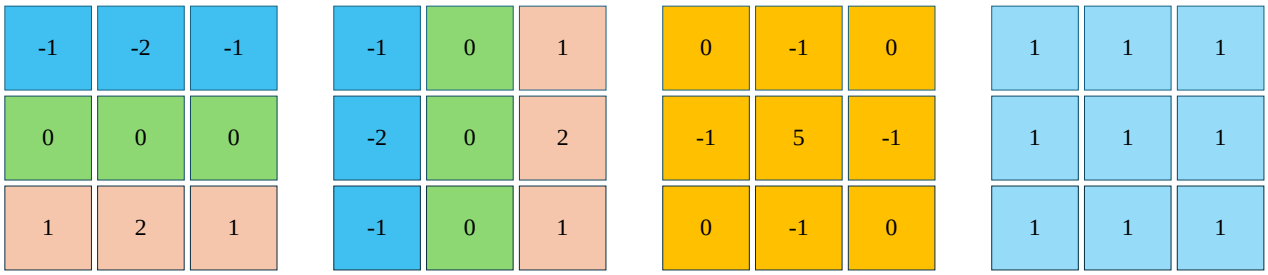
In equation (1), G represents the gradient image calculated by the Sobel operator. I_x and I_y signify the gradient images in the horizontal and vertical directions. I_h and I_l represent high-pass and low-pass filtered images, respectively. N is the adaptive parameter, dynamically adjusted according to the window size. For example, for N 3×3 filter window, $N = 9$. The role of $1/N$ is to normalize the filter coefficient to ensure that the brightness of the filtered image remains stable and avoid numerical overflow or deviation caused by different window sizes. I is the original image. The Sobel operator and filter template used in the study are shown in Figure 1.

To construct a fuzzy set of each pixel and mathematically model ambiguous pixels in the image, the study describes the fuzzy set through membership functions to determine the degree to which pixels belong to the fuzzy set. The Gaussian membership function can change its shape and width by adjusting the mean and

standard deviation parameters, making it suitable for different image processing needs, effectively smoothing the image, and reducing noise [16]. Equation (2) displays the Gaussian membership function.

$$f(x,\sigma,c)=e^{\frac{(x-c)^2}{2\sigma^2}} \quad (2)$$

In equation (2), x is the normalized gray value of the input pixel. h is the center position of the membership function, which is the average gray value of the local window of the image. σ is the standard deviation. The width of the membership function is controlled. The initial value is set at 0.2, which is dynamically adjusted according to the global gradient



Sobel operator horizontal direction template | Sobel operator vertical direction template | High-pass filter template | Low-pass filter template

Figure 1: Sobel operator and filter template.

variance of the image. e signifies the base of the natural logarithm. The membership function determines the degree to which each pixel belongs to the set, enabling the fuzzy set to be described and quantified. Fuzzy sets convert the edge information of pixels into fuzzy values through membership functions, thereby achieving edge localization and extraction [17]. The definition of a fuzzy set is shown in equation (3).

$$A=\{(\mu_A(x)), x\in X\} \quad (3)$$

In equation (3), A is the fuzzy set, which is used to describe the edge information of pixels in the image. $\mu_A(x)$ signifies the membership function. X is the specified discourse domain, that is, the original gray value is mapped to the fuzzy discourse domain through x. $\mu_A(x)$ is the designated domain of discourse. After obtaining the fuzzy set, relevant fuzzy control rules need to be established. Fuzzy control rules define the relationship between input conditions and output results through fuzzy sets, helping the control system to reason based on fuzzy logic. The description of fuzzy reasoning is shown in equation (4).

$$if\ \ x\ \ is\ \ A, then\ \ y\ \ is\ \ B \quad (4)$$

In equation (4), A represents the input condition. B represents the output result. The fuzzy rules defined in grayscale image edge detection are shown in Table 2.

The variables in fuzzy rules are fuzzy language variables. The state description of fuzzy language variables is shown in equation (5).

$$T(x)=\{-\text{high}, \text{-medium}, \text{-low}, \text{none}, +\text{none}, +\text{low}, +\text{medium}, +\text{high}\} \quad (5)$$

In equation (5), $T(x)$ is the set of language variables. $-$high , -medium , -low , none , +none , +low , +medium , and +high represent different states of input and output variables, used to describe the size of the language variables, indicating the degree to which they belong to a fuzzy set. To strengthen or weaken the tone of fuzzy language, the study uses tone operators to change the strength of fuzzy statements, so that fuzzy logic can be closer to human language and thinking patterns [18]. The membership function processed by tone operators is shown in equation (6).

$$\mu_{H_\lambda(A)}(u)=(\mu_A(u))^\lambda \quad (6)$$

In equation (6), A is a fuzzy set. u is the domain of fuzzy sets. $\mu_A(u)$ signifies the membership function of the fuzzy set A. H_λ signifies the tone operator. $H_\lambda(A)$ is another fuzzy set on the domain after $H_\lambda(A)$ processing. λ represents the change in tone. Fuzzy reasoning is the process of deriving results based on the conditions in fuzzy rules by mimicking humans when faced with fuzzy information. The Mamdani method is used for fuzzy reasoning in the study [19]. This method is shown in equation (7).

$$\mu_{R_M}(x,y)=\mu_A(x)\wedge\mu_B(y) \quad (7)$$

In equation (7), R_M represents the relationship between fuzzy sets. $\mu_{R_M}(x,y)$ represents the membership function of R_M . $\mu_A(x)$ and $\mu_B(y)$ signify the membership functions of fuzzy sets A and B on elements x and y , respectively. After the image is blurred in the early stage, it needs to be deblurred, that is, to find the accurate output value within the output range. The study uses the centroid method for deblurring, which determines the output of fuzzy inference by calculating the centroid position of the image area in the fuzzy set [20]. The calculation process of the centroid method is shown in equation (8).

$$u=\frac{\int u\cdot\mu_N(x)dx}{\int\mu_N(x)dx} \quad (8)$$

In equation (8), u is the numerical output obtained from the fuzzy set N . $\mu_N(x)$ is the membership function value of N at pixel x . When the output transformation stage of a fuzzy set is discretized, the centroid method is shown in equation (9).

$$u = \frac{\sum_{i=1}^{m} u_i \cdot \mu_N(x_i)}{\sum_{i=1}^{m} \mu_N(x_i)} \quad (9)$$

In equation (9), x_i signifies the discrete point value in the theoretic domain. m represents the quantization series after discretizing the continuous gray values, which are typically quantified by 8-bit in image processing, i. e., $m = 256$. The membership function value of the selected N is dynamically determined by the Gaussian type membership function, which can be taken in the closed interval [0, 1]. Its parameters c and σ

Table 2: Fuzzy rule set.

Serial number	**Input variable**				**Output variable**
	I_x	I_y	I_h	I_l	**Edge**
1	Medium	None	Low	None	High
2	None	Medium	Low	None	High
3	Low	None	Low	None	Low
4	Low	Low	None	None	Low
5	Medium	Medium	None	None	High
6	High	High	None	None	High
7	None	High	None	Medium	High
8	None	Medium	None	Low	Low
9	High	None	None	Medium	High
10	High	None	None	Low	Medium

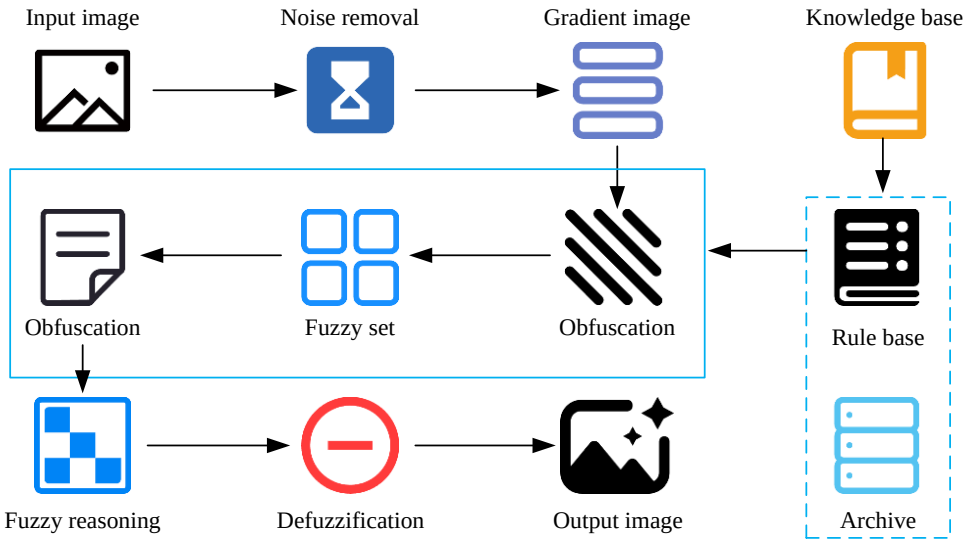


Figure 2: Fuzzy control flow in edge detection of grayscale image.

are adjusted according to the image gradient distribution and mathematical expectation. A larger gradient indicates that the function value is closer to 1, and the probability of pixels is higher. When the gradient is below the dynamic threshold, the function value approaches 0, indicating noise or non-edge areas. The fuzzy control process in grayscale image edge detection is shown in Figure 2.

In Figure 2, in the fuzzy control process, the preprocessed input image needs to be blurred first. Relevant features in the images include horizontal gradient, vertical gradient, local gray scale variation, noise intensity, gradient direction variance, and normalized gray values, which are converted into fuzzy sets through membership functions. The membership degree of each

pixel in the image is determined based on the rule library, that is, whether the pixel belongs to the edge. The results of fuzzy reasoning are transformed into clear decisions, that is, deblurring. Finally, the output image is obtained.

3.2 Edge detection algorithm based on dynamic fuzzy control

The parameter settings of the membership function and fuzzy rules in fuzzy control methods cannot be adaptively adjusted with changes in the image. Therefore, to ensure the quality of the output image, the parameters of the membership function and fuzzy rules are reset, which makes the detection process cumbersome and reduces the accuracy of the algorithm. To adaptively adjust the relevant parameters and rules based on the real-time image characteristics and environmental changes, and optimize the adaptability and accuracy, a grayscale image edge detection based on dynamic fuzzy control is built. The dynamic fuzzy control process is shown in Figure 3.

As shown in Figure 3, in dynamic fuzzy control, noise is first removed from the input image information. After filtering, gradient images and fuzzy sets are generated. According to fuzzy rules and fuzzy theory, edge control is applied to fuzzy sets. The parameters of the membership function and fuzzy rules are adaptively adjusted based on the edge information of the current image to change the membership function of subsequent input images. Finally, the fuzzy set is subjected to deblurring processing.

In dynamic fuzzy control, an adaptive median filter is taken to remove noise, which can dynamically adjust the window size according to the noise level, edge intensity, and pixel distribution. In image processing, the noise intensity may vary in different regions [21]. Adaptive median filtering dynamically adjusts the size of the filter window according to the noise level in the local region. If the local noise is higher, the filter may expand the window to remove the noise more effectively. If the noise is lower, the window can be narrowed to reduce the interference to the details of the image. Adaptive median filtering will detect the edge strength in local regions. If the local area contains strong edges, the filter will minimize the window size to avoid blurred edges. If the local area has no obvious edges, the window can be appropriately increased to remove noise. Pixel distribution includes statistical properties such as the mean and variance of pixel values. If the pixel value distribution of the local area is relatively uniform, it means that the area may be the smooth area in the image, and the window can be appropriately increased to remove noise. If the pixel value distribution is not uniform, it may indicate that the area contains complex texture or edges. Therefore, expanding the window should be avoided. The workflow of the adaptive median filter is shown in Figure 4.

From Figure 4, when using a filter to remove noise, first, the size of the filtering window is determined. Then, the minimum grayscale value $Z_{\min}$, the maximum grayscale value $Z_{\max}$, and the grayscale median value Z_{med} under the current window are calculated. The sizes of the three values are compared to determine whether Z_{med} is within $Z_{\max}$ and $Z_{\min}$. If the judgment is true, the original pixel value Z_{xy} is further determined to be within the same range. If it is within the same range, the pixel is considered not to be a noise point. Otherwise, the noise point should be replaced with Z_{med}. If the judgment is not valid, the window size is added. When the window size is larger than the maximum size $F_{\max}$, Z_{med} is used to replace the current pixel point. To address the issue of manually setting parameters in static fuzzy methods during image changes, this study takes dynamic fuzzy control to collect edge information from images. Firstly, the number of occurrences of image grayscale values within the minimum and maximum grayscale value ranges is calculated, and the first expected value of the image grayscale value is obtained [22]. The first expected value is shown in equation (10).

$$e_1 = \frac{\sum_{v_{\min}}^{v_{\max}} v \times I(v)}{\sum_{v_{\min}}^{v_{\max}} I(v)} \tag{10}$$

In equation (10), e_1 is the first expected value, which represents the minimum and maximum grayscale values. $I(v)$ signifies the number of times the grayscale value of the image appears within $v_{\min}$ and $v_{\max}$. Afterwards, the second, third, and fourth expected values are calculated separately from the first expected value. Due to the different linguistic variables in the input images, the parameters in the corresponding Gaussian membership function also change accordingly. When the fuzzy language is "*low*", the pixel value is $c = 0$, which is put into the Gaussian membership function. The expression about σ can be obtained, as shown in equation (11).

$$\begin{cases} c = 0 \\ \sigma = \dfrac{Threshold_{(low)}}{2\sqrt{3\ln^{10}}} \end{cases} \tag{11}$$

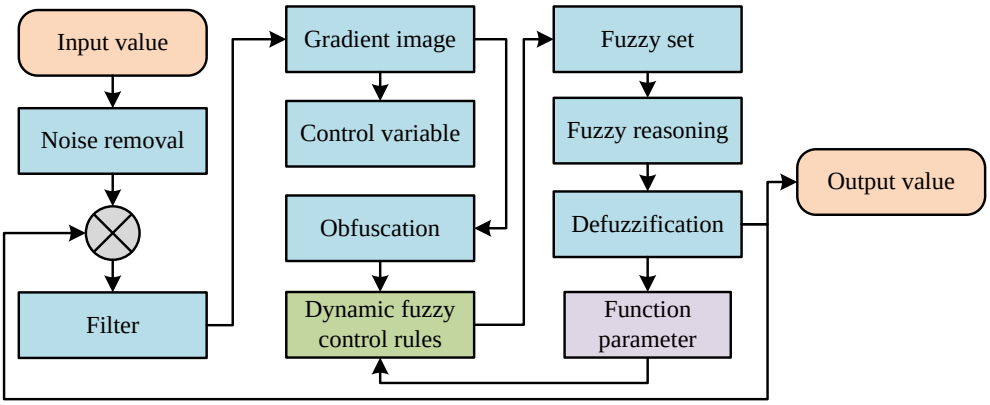


Figure 3: Flow chart of dynamic fuzzy control.

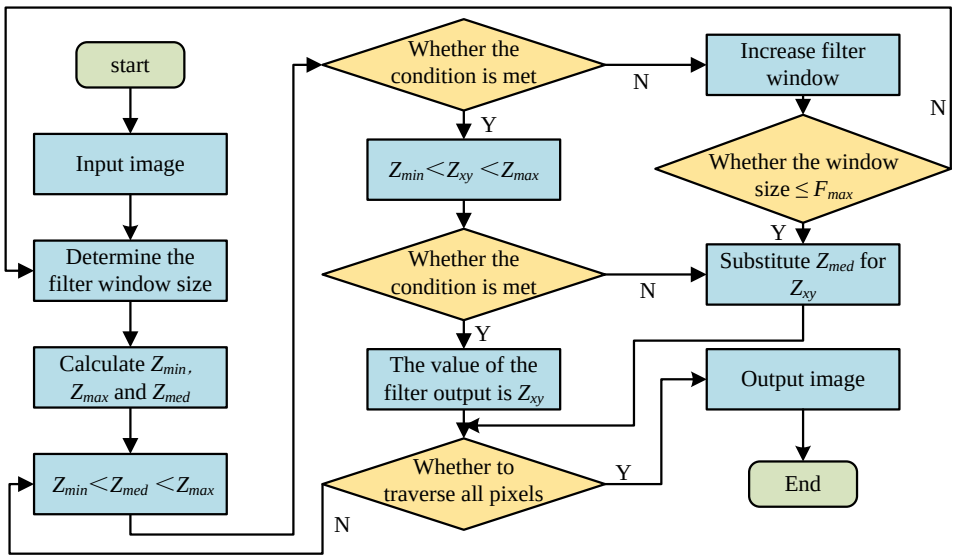


Figure 4: Flow chart of adaptive median filter.

In equation (11), c represents the pixel value. $Threshold_{(low)}$ represents the threshold when fuzzy language is "*low*". Grayscale images typically store each pixel value in 8-bit (1 byte) in a range from 0 (pure black) to 255 (pure white). The setting of the input value range [0, 255] stems from a normalized representation of the 8-bit grayscale image as an input range of the Gaussian membership function. When the fuzzy language is "*medium*" and "*high*", the pixel value is expressed as half of the maximum pixel value (127.5) and the maximum pixel value (225), respectively. When the fuzzy language is "*low*", the pixel value is $c = 0$. It is used in the Gaussian membership function to obtain the expression about σ. When the fuzzy language is "*medium*" and "*high*", the pixel value c is changed to 127.5 and 225, respectively, and then calculated according to the same equation to obtain the parameters under various fuzzy language variables [23]. The threshold *Threshold* in the above equation is shown in equation (12).

$$\begin{cases} Threshold_{(low)} = \begin{cases} e_1 & if \quad Mean_{Local} < e_1 \\ Mean_{Local} & otherwise \end{cases} \\ Threshold_{(medium)} = Mean_{Local} \\ Threshold_{(high)} = \begin{cases} e_4 & if \quad Mean_{Local} > e_4 \\ Mean_{Local} & otherwise \end{cases} \end{cases} \tag{12}$$

In equation (12), e_4 is the fourth expected value. $Threshold_{(medium)}$ and $Threshold_{(high)}$ are the thresholds for "*medium*" and "*high*" in the fuzzy language, respectively. $Mean_{Local}$ is the average grayscale value, as shown in equation (13).

$$Mean_{Local} = \frac{\sum_{x=-1}^{x=1} \sum_{y=-1}^{y=1} (x+i, y+j)}{9} \tag{13}$$

In equation (13), x and y signify the center point coordinates of the filter window. i and j are the offsets of the coordinates. To deal with the constantly changing fuzzy logic in dynamic fuzzy control, the Takagi-Sugeno

fuzzy reasoning method [24] is adopted. The reasoning process of this method is shown in equation (14).

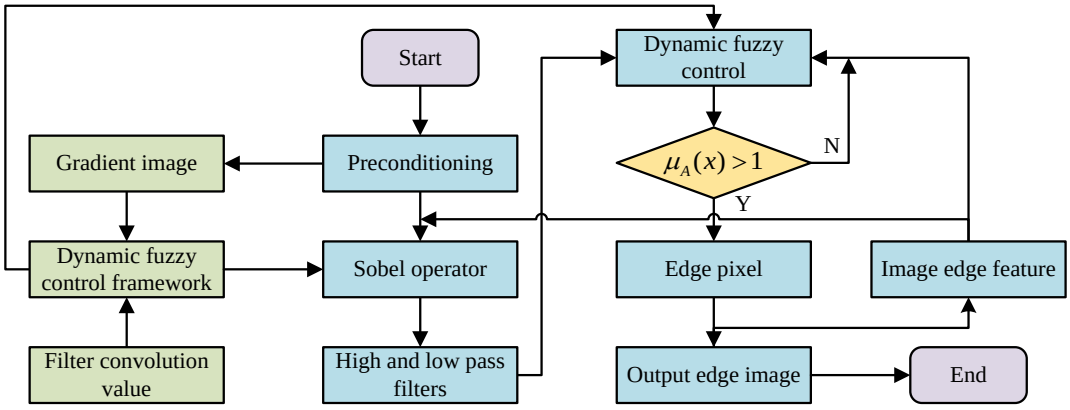


Figure 5: Flow chart of grayscale image edge detection algorithm based on dynamic fuzzy.

$$R^l: If \ \ x_1 \text{ is } F_1^l \text{ and} \cdots x_n \text{ is } F_n^l \text{ Then } x(t)=A_l x(t)+B_l u(t) \quad (14)$$

In equation (14), R^l is the approximate inference rule l in the Takagi-Sugeno method. x_1 and x_n are input variables, including the image gradient amplitude and mathematical expected value. F_1^l and F_n^l are fuzzy sets corresponding to the input variables in rule l. $x(t)$ is the state variable, representing the current state of the dynamic fuzzy control system, including image edge features, membership function parameters, and thresholds. A_l is the coefficient matrix multiplied by the input variable. B_l is the coefficient matrix multiplied by the control input variable. $u(t)$ is the control signal used to guide the edge detection process and adjust the detection strategy. After normalizing the inference fuzzy set, product inference and single point fuzzy processing are used in dynamic fuzzy control. The final state is calculated through the weighted average of the fuzzy set [25], as displayed in equation (15).

$$x(t)=A(\mu(t))x(t)+B(\mu(t))u(t) \quad (15)$$

In this algorithm, firstly, the grayscale image needs to be converted into a two-dimensional arithmetic matrix form, and an adaptive median filter is used to remove noise from the image. The Sobel operator and filter are used to obtain the corresponding gradient image. The relevant parameters of the Gaussian membership function are obtained from the gradient amplitude of the gradient image, the local window gradient mean, and the global gradient variance. The centroid method is used for deblurring fuzzy sets to obtain accurate edge image information. The Sobel operator and the window size in the filter are dynamically adjusted according to the edge information of the gray image. The relevant parameters of the Gaussian membership function are adjusted according to the expected value of the maximum gray value of the edge image. When encountering similar images in future detection, relevant parameters can be automatically set. The entire detection algorithm process is shown in Figure 5.

The fuzzy rule base is designed based on expert experience. The input variables are horizontal gradient G_x, vertical gradient G_y, local gray change, and noise intensity, and the output variable is edge probability. The value range corresponding to the fuzzy language variable in the rule is defined, as shown in equation (16).

$$\begin{cases} \text{Gradient variable:} \\ \begin{cases} Low:[0,0.3\cdot G_{\max}] \\ Medium:[0.3\cdot G_{max},0.7\cdot G_{max}] \\ High:[0.7\cdot G_{\max},G_{\max}][0.7\cdot G_{max},G_{max}] \end{cases} \\ \text{Gray change:} \\ \begin{cases} Low:[0,\ 0.2] \\ Medium:[0.2,\ 0.6] \\ High:[0.6,\ 1.0] \end{cases} \end{cases} \quad (16)$$

In equation (16), $G_{\max}$ is the maximum gradient value of the image, normalized to [0,1]. The initial value of the standard deviation σ of the Gaussian function is 0.2, which is dynamically updated according to the global gradient variance V_g of the image. The updating process is shown in equation (17).

$$\sigma = 0.2 + 0.1\cdot \tanh(V_g / 0.05) \quad (17)$$

Real-time thresholds are generated by Takagi-Sugeno fuzzy inference, whose weight coefficients are automatically calculated based on the fourth-order expected values. In the real-time processing, the membership function parameters are updated once per frame, and the fuzzy rule weights are updated once every 5 frames. The update delay is controlled within 0.5ms to ensure that the algorithm meets the real-time performance requirements. In the image gray transition problem, equation (2) is used to quantify the fuzziness of the gray gradient region. For the low-contrast region with gray difference $\Delta I < 0.15$ between adjacent pixels, the fuzzy set is dynamically divided by adjusting the standard deviation of the membership function, and the continuous gray value is mapped into three types of fuzzy states, namely weak edge, medium edge, and strong edge, to avoid the edge fracture caused by traditional hard

threshold segmentation. In the irregular shape processing problem, fuzzy rule weights are generated dynamically through Takagi-Sugeno fuzzy inference (Equation 14), gradient direction distribution of local window (equation 1), and gradient direction variance V_θ within the window. When the gradient direction variance of the irregular shape is $V_\theta > 0.1$, the weight of the gradient size rule is reduced, and the decision priority of the local gray change (equation 3) is raised, so as to avoid the edge missing detection caused by rule rigidity.

The image occlusion area processing based on fuzzy mathematics is as follows:

For the occluded region in the image, the fuzzy set $\mu_{\text{occlusion}}(I)$ of occluded object and background is modeled by the dual-modal membership function, as shown in equation (18).

$$\mu_{\text{occlusion}}(I) = \max\left(\mu_{\text{low}}(I), \mu_{\text{high}}(I)\right) \quad (18)$$

In equation (18), $\mu_{\text{low}}(I)$ and $\mu_{\text{high}}(I)$ are membership functions for low grayscale occlusion and high grayscale background, which retain potential edge information through maximization operation. In the real-time processing, the membership function parameters are updated every frame, and the fuzzy rule weights are updated every 5 frames. The update delay is controlled within 0.5ms to ensure that the algorithm meets the real-time performance requirements. The pseudo-code of the dynamic fuzzy control algorithm is shown in Figure 6.

```
Input: Grayscale image I[H][W]
Output: Binary edge map E[H][W]
1. Preprocessing:
  I_filtered ← adaptive_median_filter(I, F_max=15)   F_max: max window size
2. Gradient Computation:
  G_x, G_y ← sobel(I_filtered)   Horizontal/vertical gradients
3. Dynamic Fuzzy Control:
  for each pixel (i,j):
    Parameter adaptation (Eq.12)
    μ ← mean(G_x[i-2:i+2, j-2:j+2])      Local mean in 5×5 window
    σ ← 0.2 × (1 + |∇I_ij| / 255)        |∇I|: gradient magnitude
    Fuzzy inference (Eq.14)
    total_weight ← 0
    edge_prob ← 0
    for each rule R_k in Table1:
      μ_A ← exp( -(G_x[i][j] - c_k)² / (2σ²) )   c_k: rule center
      μ_B ← exp( -(G_y[i][j] - d_k)² / (2σ²) )   d_k: direction threshold
      w_k ← μ_A × μ_B
      edge_prob += w_k × (p_k·G_x + q_k·G_y + r_k)   TSK model
      total_weight += w_k
    Decision (Eq.8)
    E[i][j] ← 𝕀( edge_prob / total_weight > 0.7 )   𝕀: indicator function
4. Postprocessing:
        E ← morph_close(E, kernel=3×3)   3×3 structural element
```

Figure 6: The pseudo-code of the dynamic fuzzy control algorithm.

4 Results

4.1 Comparison of subjective analysis and detection efficiency

To verify the proposed algorithm, comparative experiments are conducted with the improved fuzzy control algorithm and commonly used edge detection algorithms to assess the performance. The fuzzy control algorithm and Canny algorithm are from [8] and [11], the edge detection method based on Dense Residual Network (DRN) is from reference [26], and the Sobel algorithm and Robert algorithm are from reference [27]. All algorithms are tested under the same conditions. The central processing unit of the desktop computer used in the experiment is Intel Core i5-10700K, the operating system is Windows 10 Professional 64-bit, and the software environment is MATLAB R2023. The experimental dataset is BSDS500, which contains 500 grayscale images covering various scenes, including complex textures, low contrast, and noise interference. The training, validation, and test sets have 200,100, and 200 images, respectively. The input images are also normalized to the [0, 1]. The detailed experimental environment parameters are shown in Table 3. The maximum window size of the adaptive median filter is 15, the initial value of the standard deviation of the Gaussian membership function is 0.2, the upper limit of the parameter update delay is 0.5ms, the fuzzy rule update frequency is 5 frames per time, and the edge determination threshold is 0.7. The fuzzy control algorithm proposed in the study and the improved dynamic fuzzy control algorithm are used to perform edge detection on the two grayscale images listed. Three commonly used edge detection algorithms are compared to subjectively analyze the generated edge images. In the BSDS500 dataset, the edge detection images obtained by various methods are shown in Figure 7.

Table 3: Parameter information of model training test platform.

Hardware facility		Software facility	
Device CPU	Intel Core i5-10700K	Operating system	Windows 10 Professional 64-bit
Device graphics card	NVIDIA GeForce RTX 3060 12GB	Programming language	Python 3.6
Storage device	SSD 1TB NVMe	Programming environment	MATLAB R2023a
Network interface	Gigabit Ethernet	Simulation and testing tools	Jupyter Notebook
Internal memory	32GB DDR4	Image processing toolkit	MATLAB Image Processing Toolbox

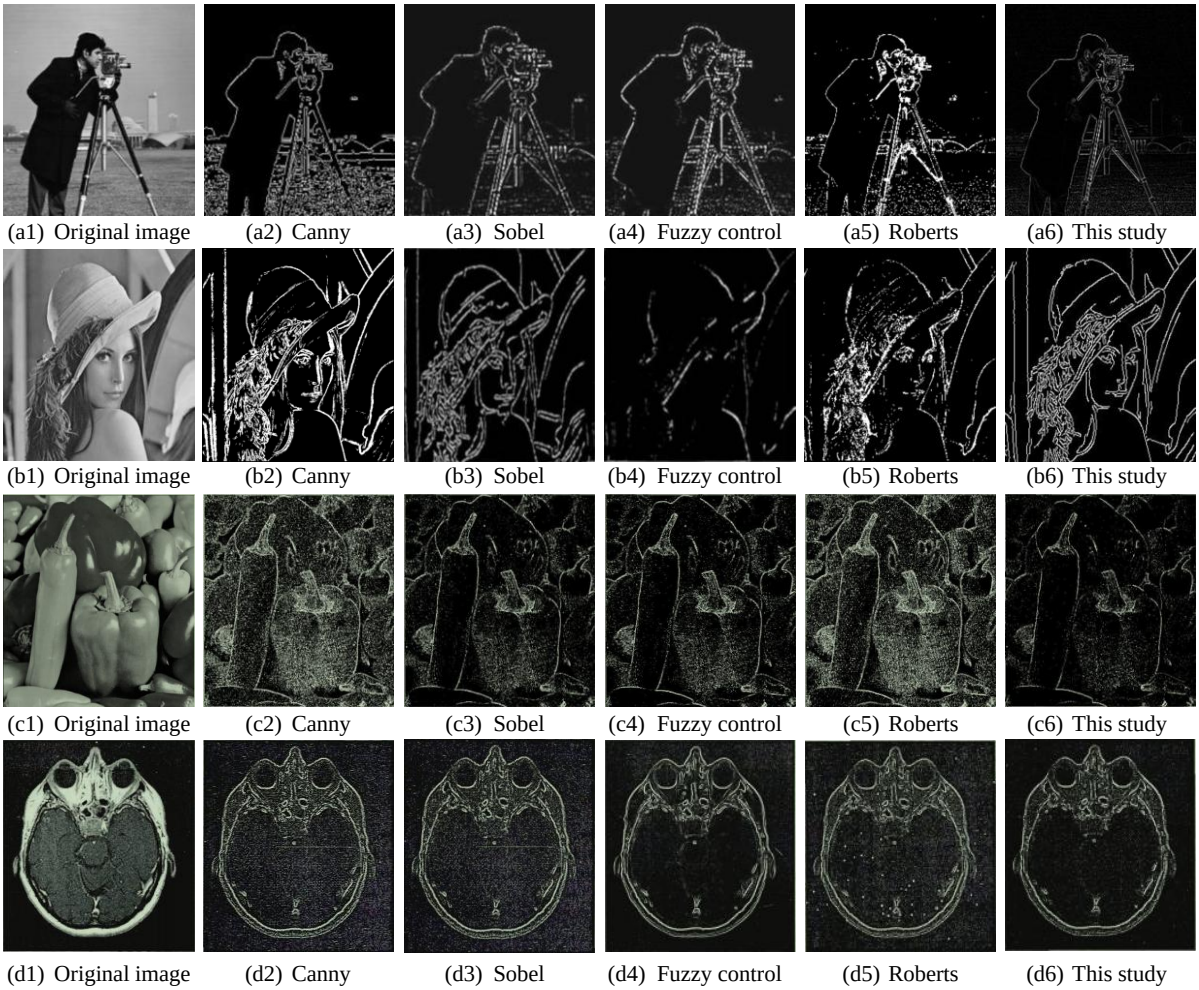
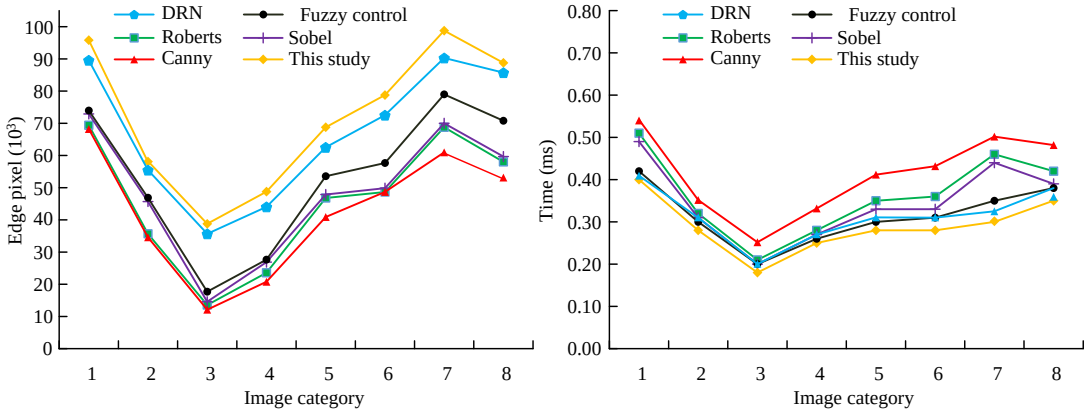


Figure 7: Different methods for detecting edge images based on the original image.



(a)The number of edge pixels extracted by each method

(b) The extraction time of image edge pixels of each method

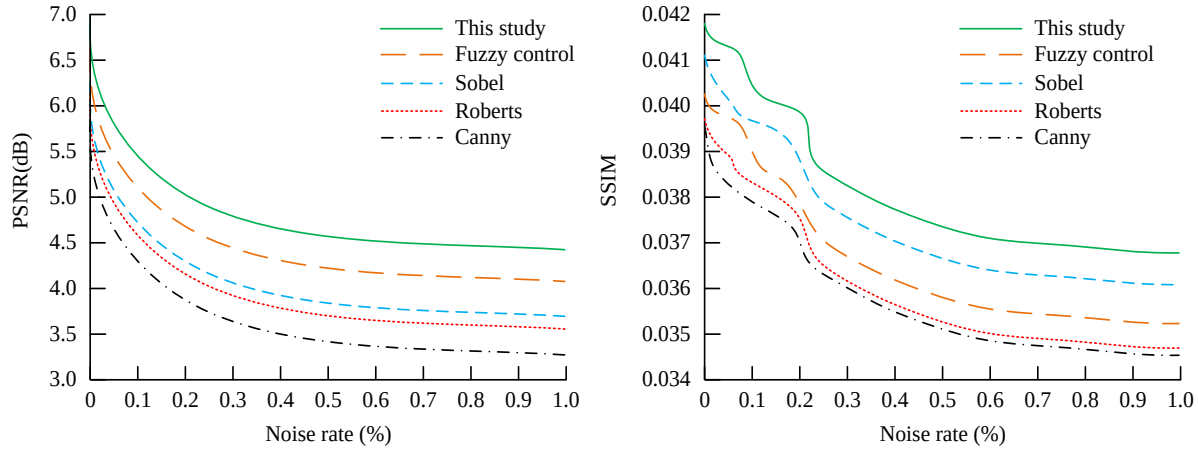
Figure 8: Each method for detecting the number of edge points and detection time.

In Figure 7, from images c2, b5 and a4, the detected images obtained by Canny, Roberts and Sobel algorithms appeared, and the edge image quality extracted by these three algorithms was significantly lower than that of images d2, d5 and d4. From the image b4, the edge detection method based on static blur control exhibited edge information loss without more pseudo edges and isolated points. Therefore, compared with other methods, the optimized algorithm can effectively detect the real edges of the image. From images a6 and b6, the lines were extracted with clear and smooth edges, which were close to the original image, and the noise was reduced to a large extent. To further compare the detection performance of various methods, this study compares the above methods and the latest edge detection method based on DRN. The number of edge points extracted during the edge detection of 8 types of grayscale image and the time required for the detection process. The statistical results are shown in Figure 8.

Figure 8 (a) shows the number of edge points extracted by each method, and Figure 8 (b) shows the time required for the detection process. In Figure 8 (a), the difference in the number of edge points extracted by Canny, Roberts, and Sobel algorithms in various types of images was relatively small. The optimized method can extract more edge points from all categories of images. Compared with before optimization, the number of detected edge points was increased by 32.78%. Compared with DRN, the research method extracted more number of edge points in different categories of images, and the average number of edge points increased by 7.52×10^3. As shown in Figure 8 (b), the detection time of the research method was the lowest, with an average time of 0.30ms, which was 4.76% shorter than before optimization, 27.04% shorter than Canny algorithm, 17.53% shorter than Roberts algorithm, and 13.04% shorter than Sobel algorithm. This research method required a shorter time to extract images of different categories, reducing the average detection time by 0.18ms. From this, the method proposed in the study has a relatively accurate detection effect and high computational efficiency.

4.2 Comparison of edge detection capability and resource utilization rate

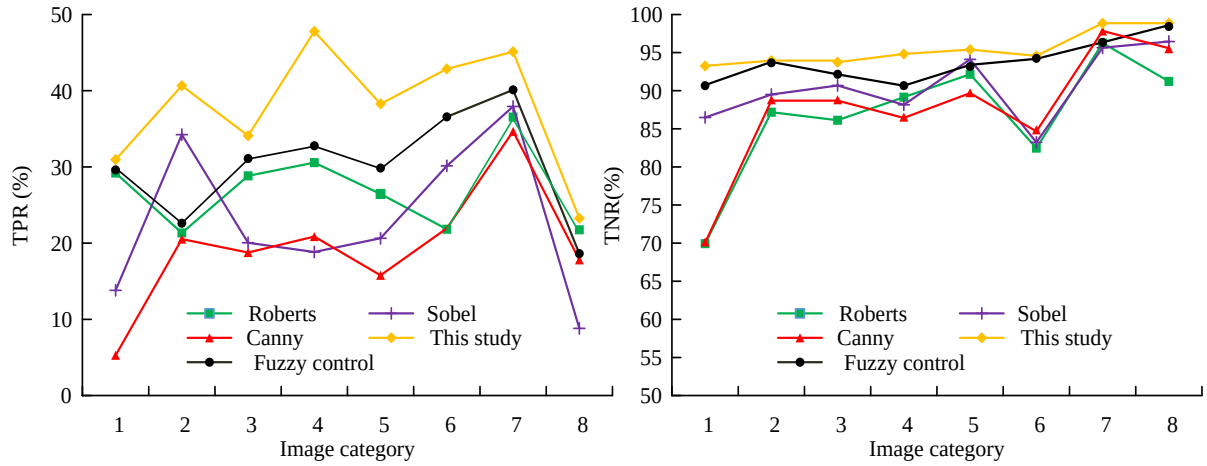
To further objectively analyze the performance, the Structural Similarity Index (SSIM) and PSNR between the original grayscale image and the edge image are compared. PSNR is an objective metric for measuring the difference between two images. A high value indicates that the error between the reconstructed image and the original image is small, that is, indicating better image quality. SSIM is a quality evaluation metric applied to assess the similarity between two images, focusing on the structural information and better reflecting the perception of the human visual system. The PSNR and SSIM changes of each method are displayed in Figure 9. Figure 9 (a) shows the PSNR change curve of each method under different noise levels, and Figure 9 (b) shows the SSIM change curve of each method under different noise levels.



(a) Each method in PSNR curves under different noise levels

(b) Each method in SSIM curves under different noise levels

Figure 9: PSNR and SSIM change curve with noise level.



(a) TPR of image edge detection by each algorithm

(b) TNR of image edge detection by each algorithm

Figure 10: TPR and TNR for image edge detection by each algorithm.

In Figure 9 (a), the PSNR of various methods rapidly decreased before the noise level reached 0.3%, and then showed a gradually slow decreasing trend. The curve of the Canny algorithm was located at the bottom, demonstrating that there was an obvious difference and severe distortion between the edge image and the original image. With the increase of noise level, the PSNR of the research method was always higher than other methods, and the PSNR at the maximum noise level was 4.43dB, indicating that this method had lower distortion compared to other methods and was more similar to the original image. In Figure 9 (b), the proposed method had a higher SSIM compared to other methods. However, in high noise environment (Noise rate=1%), PSNR and SSIM decreased to 4.43 dB and 0.0367, respectively. This is because the maximum window size of the adaptive median filter cannot cover the cluster distribution area of high-intensity pulse noise, resulting in residual noise. Meanwhile, the membership function of dynamic fuzzy rule is frequently adjusted by noise interference, causing the misjudgment rate of low gradient state in the rule base, thereby disrupting edge continuity. In general, there is high similarity between the edge image and the original image. The study evaluates the binary classification ability of various algorithms through sensitivity (TPR) and specificity (True Negative Rate, TNR). The average values of TPR and TNR when detecting different images by each method are shown in Figure 10.

Figure 10 (a) shows the TPR statistics of the detection results of different categories of images by each method, and Figure 10 (b) shows the TNR statistics of the detection results of different categories of images by each method. In Figure 10 (a), various types of images had different features, resulting in significant variations in TPR for each method. The research method achieved high TPR in edge detection of various categories of images, and could accurately classify foreground pixels in the image. The highest TPR was 47.79% when processing image 4. In image category 8, the TPR of low contrast blurred images (medical X-rays) decreased to 22.63%, mainly due to insufficient response of dynamic blur rules to weak gradients, resulting in edge continuity fracture. From Figure 10 (b), the research method had the highest TNR for edge detection of various types of images, and was

more accurate in determining non-edge points in the images. The TNR was the highest when processing image 8, which was 98.87%. In image category 1, the TNR of high-frequency texture interference images (forest remote sensing images) was relatively low, at 93.26%, due to the limitation of the adaptive median filtering window size, which completely suppressed dense texture noise. Further experiments showed that when the local gradient standard deviation of images was below 5, the dynamic parameter adjustment delay was about 0.5ms, resulting in the membership function being unable to adapt to the changes in local features over time. In general, the research method has good binary classification ability in edge detection. The hardware resource utilization of various algorithms in the image edge extraction is shown in Table 4. The hardware resources in Table 4 are Lookup Table Random Access Memory (LUTRAM), Flip-Flop (FF), Lookup Table (LUT), and Block Random Access Memory (BRAM).

Table 4: The consumption of hardware resources of each part of the system by different algorithms.

Hardware resource			**LUTRAM**	**FF**	**LUT**	**BRAM**
Available resource			6000	35500	17800	60
Detection method	Canny	Utilized resources	617	4256	3614	5.8
		Resource Utilization (%)	10.28%	11.99%	20.30%	9.67%
	Roberts	Utilized resources	482	3566	3083	4.3
		Resource Utilization (%)	8.03%	10.05%	17.32%	7.17%
	Sobel	Utilized resources	450	3083	2540	4.1
		Resource Utilization (%)	7.50%	8.68%	14.27%	6.83%
	Fuzzy control	Utilized resources	395	2862	2137	3.4
		Resource Utilization (%)	6.58%	8.06%	12.01%	5.67%
	This study	Utilized resources	236	2137	1500	3.2
		Resource utilization (%)	3.93%	6.02%	8.43%	5.33%

According to Table 4, the total hardware resource utilization rate of the fuzzy control method was 32.32%. The research method showed that the resource utilization rates of lookup table memory, storage, lookup table, and block random access memory were 3.93%, 6.02%, 8.43%, and 5.33%, respectively. The total hardware resources of the system accounted for 23.71%, which was 8.61% lower than before optimization. On the Xilinx Zynq-7020 FPGA platform, the algorithm increased from 28 fps to 35 fps, meeting the real-time video processing requirements (30 fps). Power consumption test showed that the energy efficiency ratio of the dynamic fuzzy control module was 3.2 GOPS/W, which was 77.81% higher than the traditional Canny algorithm (1.8 GOPS/W). It is suitable for UAV navigation and other low-power scenarios. In the NVIDIA Jetson Nano embedded device, the memory footprint decreased from 412MB before optimization to 327MB, supporting the simultaneous execution of other image analysis tasks such as object detection. From this, the research method can complete image processing with low hardware resource consumption.

5 Discussion

The dynamic fuzzy control edge detection method presented in this paper shows significant advantages in performance index, adaptability, and resource efficiency. Experimental data showed that on the BSDS500 dataset, the PSNR of the proposed method under the maximum noise (0.5%) reached 4.43dB, which was significantly better than the sharp-guided filtering method proposed by Raheja S (reference [11], PSNR=3.50dB) by 26.57%. The SSIM was 0.0367, which was 7.94% higher than that of the Canny fuzzy logic method proposed by Kumawat A (reference [10], SSIM=0.0340), verifying its advantage in preserving image structure information. In addition, the TPR of the proposed method reached 47.79%, 25.76% higher than 38.00% in reference [5]. The TNR maintained at 98.87%, which was superior to Guided L0 smoothing filtering method designed by Kumar A (reference [13], TNR=98.50%) by 0.37%. These improvements benefit from the adaptive mechanism of dynamic fuzzy rules. The membership function parameters are adjusted in real-time by Takagi-Sugeno fuzzy reasoning, which solves the edge

breakage caused by fixed rules in traditional fuzzy methods (e.g., reference [10]). The adaptive median filter is combined to dynamically adjust the window size and retain the edge details in the denoising, avoiding the core defect of the sensitivity of the sharpening filter to noise in reference [11]. Compared with the baseline, the number of edge points detected by the research method was increased by 32.78%. This is due to the synergistic effect of dynamic fuzzy rules and noise perception parameter optimization strategies: adaptive modeling based on fourth-order expected values using grey distribution, and precise compression of computing resources through centroid deblurring.

However, in a rapidly changing image sequence, the update frequency of dynamic parameters may not fully match the changing speed of the scene, resulting in transient performance fluctuations. In addition, although the resource usage of the proposed method is low, its dynamic inference process still relies on floating point operation, which may face the computing power bottleneck in low-end hardware. Nevertheless, this method provides an efficient and reliable edge detection solution for real-time image processing through the collaborative design of dynamic fuzzy control and noise robustness optimization.

6 Conclusion

To achieve accurate edge localization of grayscale images, a grayscale image edge detection algorithm based on fuzzy control was designed. A dynamic fuzzy control was designed to address the fuzzy rule and parameter not being able to be adaptively adjusted. The edge images generated by different methods, the number of edge points extracted during the detection process, and the detection time were compared. The relevant evaluation indicators and system resource utilization of edge images were compared. The results indicated that the edge image obtained by the research method was relatively close to the original image, with clear and smooth lines. The average number of edge points detected by the research method was 78329, which was 32.78% higher than the fuzzy control method before optimization. The average detection time was 0.30ms, which was 4.76% shorter than before optimization, 27.04% shorter than Canny algorithm, 17.53% shorter than Robert's algorithm, and 13.04% shorter than Sobel algorithm. The PSNR at maximum noise level was 4.43dB, and the SSIM was 0.0367. The maximum values of TNR and TPR were 47.79% and 98.87%, respectively, both higher than the other four methods. The research method can accurately process edge images with low system resource utilization, improving the adaptability and robustness of the edge detection method. The fuzzy rules in the research method are formulated based on the experience of relevant experts. Over reliance on complex fuzzy rules in the edge detection process also increases the complexity of the algorithm. Future research will further optimize the fuzzy rules and design more concise and effective algorithms.

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Efficient Transformer Architectures for Diabetic Retinopathy Classification from Fundus Images: DR-MobileViT, DR-EfficientFormer, and DR-SwinTiny

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Diabetic retinopathy (DR) is a prevalent cause of vision loss, necessitating efficient diagnostic tools, particularly in resource-limited settings. This study presents three lightweight transformer-based models—DR-MobileViT, DR-EfficientFormer, and DR-SwinTiny—for automated DR classification from fundus images (APTOS 2019: 3,662 images; Messidor-2: 1,748 images). After preprocessing including resizing to 224×224 pixels and CLAHE enhancement, these models, leveraging compact architectures (1.8–3.5M parameters), are trained using an AdamW optimizer with data augmentation. DR-MobileViT integrates convolutional and transformer layers, DR-EfficientFormer employs a dimension-consistent design, and DR-SwinTiny utilizes shifted window attention. All models were initialized with ImageNet pretrained weights. Evaluated on the APTOS 2019 and Messidor-2 datasets, they achieve quadratic weighted kappa (QWK) scores up to 0.89 and areas under the ROC curve (AUC) up to 0.95. These models approach the performance of top-performing CNN ensembles from the APTOS 2019 challenge (which exceed 40M parameters) while reducing inference times to 10–15 ms/image (NVIDIA P100 GPU) and computational overhead by over 90%. These results indicate their potential for scalable, point-of-care DR screening, offering a viable solution for early detection in underserved regions.

Povzetek: Članek predstavi tri lahke transformerje (DR-MobileViT, DR-EfficientFormer, DR-SwinTiny) za klasifikacijo diabetične retinopatije, ki dosežejo dober QWK ob več kot 90% nižji računski obremenitvi glede na SOTA CNN.

1 Introduction

Diabetic retinopathy (DR) is a microvascular complication of diabetes mellitus, affecting approximately one-third of diabetic patients and posing a significant risk of blindness if undetected [1]. Early diagnosis through retinal screening is critical, yet access to expert ophthalmologists and advanced imaging systems is limited in low-resource settings. Automated detection systems using fundus photography and deep learning have emerged as viable solutions [2], with convolutional neural networks (CNNs) dominating recent advancements [4]. However, the computational complexity of state-of-the-art CNNs, such as those topping the APTOS 2019 Blindness Detection challenge [5], renders them impractical for deployment on resource-limited devices like mobile phones or low-cost hardware.

The advent of transformer architectures, originally developed for natural language processing [7], has revolutionized computer vision tasks, including medical image analysis [9]. Transformers leverage attention mechanisms to capture long-range dependencies, offering superior feature extraction compared to CNNs in some contexts [10]. Despite their success, standard transformer models, such as Vision Transformer (ViT) [10], are parameter-heavy and computationally demanding, limiting their utility in real-world clinical applications. Recent efforts to design lightweight transformers, such as MobileViT [12], EfficientFormer [13], and Swin Transformer variants [14], have shown promise in balancing performance and efficiency, making them attractive for medical diagnostics [15].

This study proposes a suite of lightweight transformer-based models tailored for DR detection from fundus images. Our approach prioritizes compactness and speed, targeting deployment in point-of-care settings. We benchmark these models against the top three winners of the APTOS 2019 challenge—deep CNN ensembles with millions of parameters—using the publicly available APTOS 2019 dataset and an external test set from the Messidor-2 dataset. Execution is performed on a Kaggle-provided NVIDIA P100 GPU, ensuring accessibility to reproducible computational resources. Our results indicate the potential of achieving high diagnostic accuracy with significantly re-

duced computational footprints, paving the way for scalable DR screening solutions.

2 Related works

Automated detection of diabetic retinopathy has been a focal point of medical imaging research, with significant advancements driven by deep learning. Early efforts utilized traditional CNNs, such as VGG and ResNet architectures, to classify DR severity from fundus images [3, 17]. Gulshan et al. demonstrated the potential of Inception-v3 for DR detection, achieving an AUC of 0.99 on a proprietary dataset, though the model's size (over 20 million parameters) limited its practical deployment [3]. The APTOS 2019 Blindness Detection challenge further advanced the field, with top solutions employing large-scale CNN ensembles (e.g., ResNet-50, DenseNet-121) to achieve quadratic weighted kappa (QWK) scores above 0.90 [5, 18, 19, 20]. However, these models, with parameter counts exceeding 30 million, are computationally prohibitive for resource-constrained environments [6]. Contributions from the journal *Informatica* also highlight work in this area, such as Zhang et al. [39] who proposed an optimized CNN framework achieving high accuracy on MESSIDOR and IDRiD datasets, and Poranki et al. [40] who developed DRG-Net using graph learning and XGBoost, reporting excellent performance on EyePACS and Messidor.

Recent studies have explored lightweight CNNs to address this limitation. Howard et al. introduced MobileNets, reducing parameters to under 4 million while maintaining reasonable accuracy for general image classification [6]. In the DR context, Pratt et al. adapted MobileNet for fundus image analysis, reporting a QWK of 0.82 with significantly lower computational cost [21]. Despite these advances, CNNs struggle to capture global contextual information, a gap addressed by transformer-based models [10]. Dosovitskiy et al.'s Vision Transformer (ViT) marked a paradigm shift, leveraging self-attention for image recognition, but its 86 million parameters render it impractical for mobile applications [10, 11].

Lightweight transformer variants have emerged to bridge this gap. MobileViT combines convolutional and transformer layers, achieving competitive performance with 2–5 million parameters [12]. EfficientFormer optimizes transformers by a dimension-consistent design, reducing FLOPs while preserving accuracy [13]. Swin Transformer introduces hierarchical attention via shifted windows, with smaller variants like Swin-Tiny offering a balance of performance and efficiency [14]. In medical imaging, Chen et al.'s TransUNet applied transformers to segmentation tasks, while He et al. surveyed their broader utility, noting potential in diagnostics [8, 15]. Recent advancements include TransMed, which integrates multi-modal data for enhanced DR detection [33], and MobileViT-v2, a further optimized transformer with improved latency on edge devices [34].

Further developments in 2023–2025 have advanced lightweight ViTs for DR detection. Yang et al. proposed VMLRI, a ViT with Masked Autoencoders (MAE) pretrained on over 100,000 fundus images, achieving an AUC of 0.9825 on the APTOS dataset with fewer parameters than traditional ViTs [35]. Ait Kaci Azzou et al. introduced a fine-tuned ViT with optimized preprocessing, reporting a QWK of 0.935 for early DR detection, emphasizing clinical relevance with only 3.2M parameters [36]. Ikram et al.'s ResViT FusionNet combines ViTs with residual connections, achieving a QWK of 0.92 on Messidor-2, with a focus on explainable AI for clinical trust [37]. Nazih et al. developed a ViT model for DR severity prediction, achieving a QWK of 0.90 with 4.5M parameters, tailored for fundus photography-based diagnosis [38]. Our study builds on these lightweight architectures, aiming to provide efficient alternatives with significantly reduced parameter counts compared to traditional CNN ensembles while maintaining high diagnostic accuracy for DR screening.

To clarify the limitations of prior SOTA models and set the context for our work, Table 1 summarizes key studies in DR detection, comparing their methods, datasets, performance metrics (QWK/AUC/Accuracy), and parameter counts. This comparison underscores the high computational demands of many existing high-performing models.

3 Proposed models and methodology

3.1 Datasets

The primary dataset for this study is the APTOS 2019 Blindness Detection dataset [17], comprising 3,662 fundus images labeled for DR severity on a scale from 0 (no DR) to 4 (proliferative DR). Images were acquired from diverse clinical settings in India, reflecting real-world variability in quality and illumination. The APTOS 2019 dataset exhibits some class imbalance, with fewer images in the more severe DR categories. For external validation, we used the Messidor-2 dataset [16], containing 1,748 high-resolution fundus images with expert-annotated DR grades. The APTOS 2019 dataset was chosen as it is a widely recognized benchmark from a recent public challenge, while Messidor-2 serves as a common, publicly available dataset for external validation, offering diversity in image characteristics. Future work could extend evaluation to other public datasets (e.g., EyePACS, DDR).

Both datasets were preprocessed by resizing images to 224×224 pixels, normalizing pixel values to [0, 1], and applying contrast-limited adaptive histogram equalization (CLAHE) [22] to enhance vascular visibility. Sample fundus images representing the range of DR severity levels from both datasets are shown in Fig. 1.

3.2 Proposed models

We developed and evaluated three lightweight transformer-based architectures, adapted for the DR classification task. The general architectures of these models are depicted in

Table 1: Summary of selected prior state-of-the-art models for diabetic retinopathy detection

Author(s)	Year	Method	Dataset(s)	QWK/AUC/Acc.	#Parameters (M)
Gulshan et al. [3]	2016	Inception-v3	Proprietary	-/0.99/-	>20
Pratt et al. [21]	2019	MobileNet	APTOS 2019	0.82/-/-	<4
APTOS Rank 1 [18]	2019	ResNet-50 + DenseNet-121	APTOS 2019	0.91/0.96/-	≈45
APTOS Rank 2 [19]	2019	Inception-v4	APTOS 2019	0.88/0.94/-	≈42
Tan et al. [20]	2019	EfficientNet-B5	APTOS 2019	0.87/0.93/-	≈30
Zhang et al. [39]	2021	Optimized CNN (Cuckoo Search)	MESSIDOR, IDRiD	-/-/97.55% (Mess.)	Custom CNN
Yin et al. [33]	2023	TransMed	APTOS 2019	0.90/0.95/-	≈25
Nazih et al. [38]	2023	ViT model	Public	0.90/-/-	4.5
Poranki et al. [40]	2024	DRG-Net (DGCN+XGBoost)	EyePACS, Messidor	-/-/99.01% (EyePACS)	Pipeline
Mehta et al. [34]	2024	MobileViT-v2	Messidor-2	0.86/0.93/-	≈3
Yang et al. [35]	2024	VMLRI (ViT+MAE)	APTOS	-/0.9825/-	< Trad. ViTs
Ait Kaci Azzou et al. [36]	2025	Fine-tuned ViT	Custom/Public	0.935/-/-	3.2
Ikram et al. [37]	2025	ResViT FusionNet	Messidor-2	0.92/-/-	Not specified

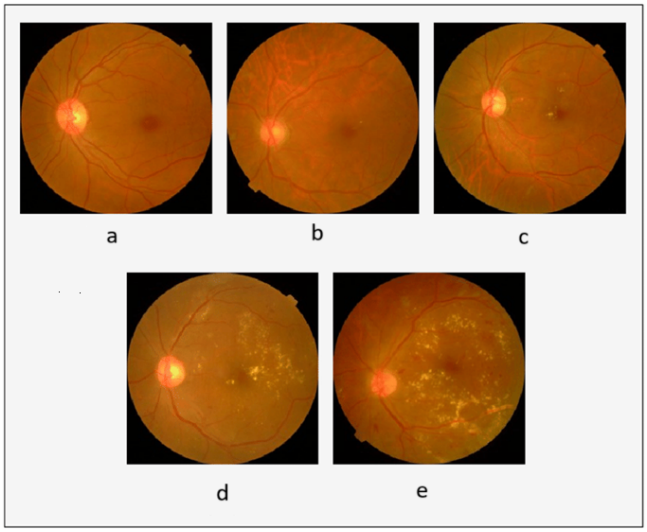


Figure 1: Sample fundus images illustrating DR severity levels: (a) No DR, (b) Mild, (c) Moderate, (d) Severe, (e) Proliferative, from APTOS 2019.

Fig. 2. All models were initialized with weights pretrained on ImageNet [4] and then fine-tuned on the DR datasets. Each model processes 224×224 RGB fundus images, outputting a 5-class probability distribution corresponding to DR severity levels.

- **DR-MobileViT**: An adaptation of the MobileViT .5 variant [12], combining an initial convolutional stem with MobileViT blocks (hybrid convolution-transformer layers) for local and global feature extraction, followed by global pooling and a classification head. It has 8 effective transformer layers with an embedding dimension of 144.
- **DR-EfficientFormer**: Based on the EfficientFormer L1 variant [13], this model uses patch embedding followed by a series of 4 EfficientFormer stages (MetaFormer blocks) with scaling embedding dimensions (48 to 320). It employs global pooling and an MLP for classification.
- **DR-SwinTiny**: This model is based on the Swin Transformer Tiny variant [14]. It starts with patch partitioning (initial patch size 4×4) and linear embedding, followed by Swin Transformer stages utilizing shifted window attention (window size 7), patch merging layers, global average pooling, and a classification head. The initial embedding dimension is 96.

Further architectural details regarding parameter counts, GFLOPs, and specific layer configurations are summarized in Fig. 2 and Table 2.

3.3 Benchmark models

We compared our models to the reported performance of the top three APTOS 2019 challenge winners, as detailed in public leaderboards and associated materials:

- **Rank 1 (CNN-Ensemble)** [18]: A blend of ResNet-50 and DenseNet-121 with approximately 45 million parameters.
- **Rank 2 (Inception-v4)** [19]: A fine-tuned Inception-v4 model [25] with approximately 42 million parameters.
- **Rank 3 (EfficientNet-B5)** [20]: An EfficientNet-B5 architecture with approximately 30 million parameters.

3.4 Training details and evaluation metrics

The APTOS 2019 dataset was split into a training set (80%, approximately 2,930 images) and a test set (20%, 732 images). A further 10% of the training data was held out as a validation set for hyperparameter tuning and model selection. The Messidor-2 dataset (1,748 images) was used entirely for external testing.

Models were trained on a Kaggle-provided NVIDIA P100 GPU using PyTorch 1.12. The training data was augmented with random rotations (±30 degrees), horizontal

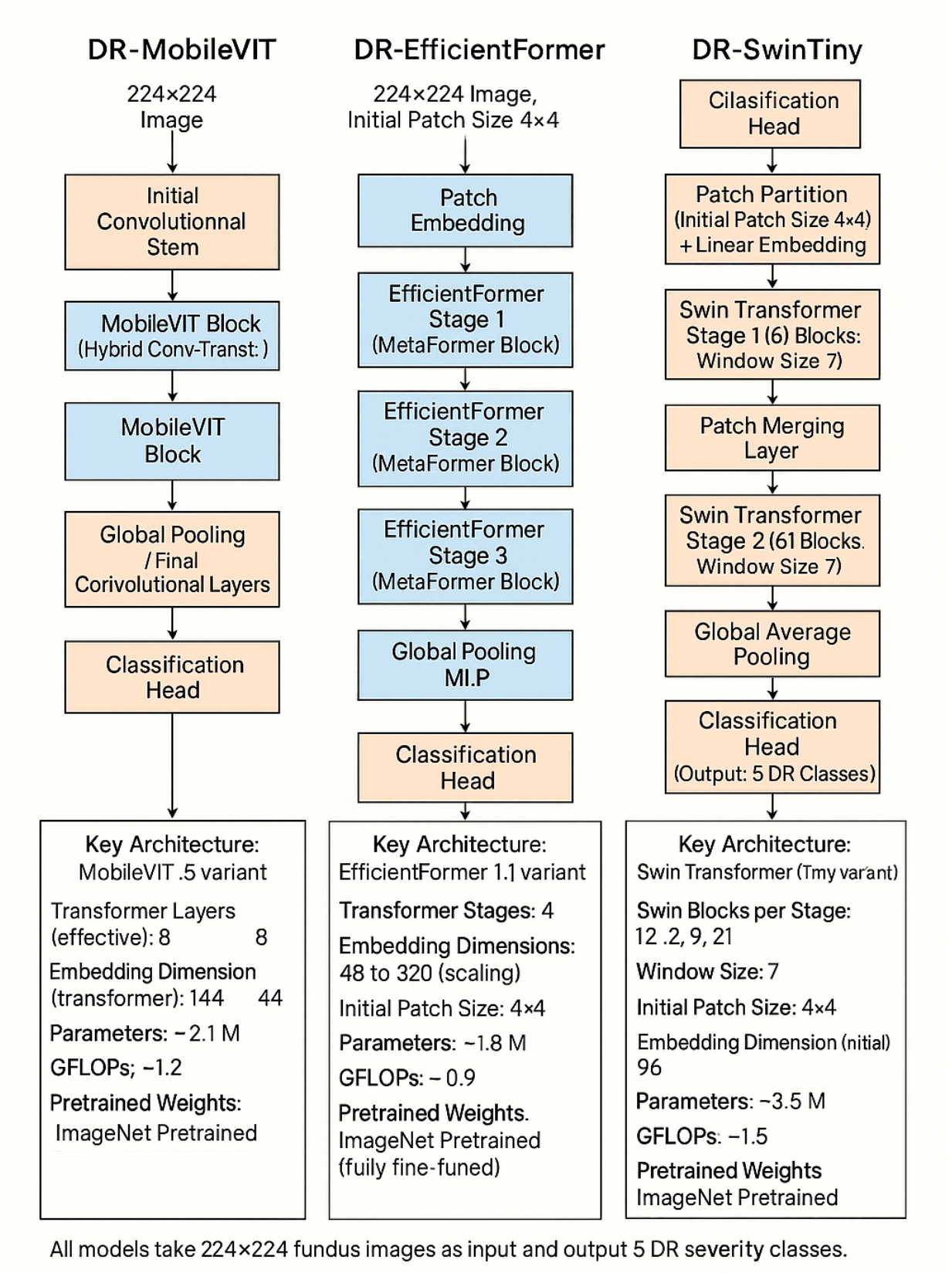


Figure 2: Architectural overview of the proposed lightweight transformer models: DR-MobileViT, DR-EfficientFormer, and DR-SwinTiny, including key parameters and pretraining strategies. (Note: All models are ImageNet pretrained as per final clarification from authors. Please ensure your diagram reflects this for DR-MobileViT as well).

Table 2: Architectural details and computational cost of proposed models. Inference time measured per image, averaged over a batch of 32 on an NVIDIA P100 GPU. All models use ImageNet pretrained weights.

Model	Variant Basis	Params (M)	GFLOPs	Infer. Time (ms/image)	Pretrained Weights
DR-MobileViT	MobileViT .5	≈2.1	≈1.2	12	ImageNet
DR-EfficientFormer	EfficientFormer L1	≈1.8	≈0.9	10	ImageNet
DR-SwinTiny	Swin-Tiny	≈3.5	≈1.5	15	ImageNet

flips, and brightness adjustments (factor 0.8-1.2) [23]. We used the AdamW optimizer [24] with an initial learning rate of 2e-4 and weight decay of 0.01, coupled with a cosine annealing learning rate scheduler over 50 epochs. The training batch size was 32. The loss function was cross-entropy with label smoothing (smoothing factor 0.1), which can also offer some robustness to class imbalance. All models were initialized with ImageNet pretrained weights sourced from their respective official implementations and subsequently fine-tuned on the DR datasets. The model checkpoint achieving the highest Quadratic Weighted Kappa (QWK) on the validation set was selected for final evaluation on the test sets.

Evaluation metrics included QWK, Area Under the ROC Curve (AUC) (macro-averaged for multi-class), sensitivity (recall), and specificity for detecting referable DR (grades 2-4 vs. 0-1) and severe DR (grades 3-4 vs. 0-2). Inference time (ms/image) and GFLOPs were measured with a batch size of 32 on the NVIDIA P100 GPU.

3.5 Statistical analysis

To ensure robustness, all training and evaluation procedures were conducted five times using different random seeds. The reported performance metrics (QWK, AUC, Sensitivity, Specificity) for the proposed models are averages over these five runs. Standard deviations were calculated and are available upon request but omitted from tables for brevity. Performance differences between models were assessed using paired t-tests with a significance level of $p < 0.05$.

4 Results

4.1 Performance on APTOS 2019 test set

Table 3 summarizes the performance of our proposed lightweight transformer models compared to the benchmark CNN models on the APTOS 2019 test set (732 images). DR-MobileViT achieved the highest QWK of 0.89 and an AUC of 0.95, closely approaching the performance of the Rank 1 CNN-Ensemble (QWK 0.91, AUC 0.96) despite having approximately 95% fewer parameters. DR-EfficientFormer and DR-SwinTiny also demonstrated strong performance, with QWK scores of 0.87 and 0.88, respectively. All proposed models achieved sensitivity exceeding 0.90 for detecting severe DR. The ROC and Precision-Recall curves in Fig. 3(a) and Fig. 3(b) visually illustrate the competitive discriminative power of our models, particularly DR-MobileViT. Confusion matrices for DR-MobileViT on the APTOS 2019 test set are shown in Fig. 4(a).

4.2 External validation on Messidor-2

To assess generalization capabilities, the models were evaluated on the Messidor-2 dataset. As shown in Table 4, DR-MobileViT maintained robust performance with a QWK of 0.87 and an AUC of 0.93. This compares favorably to the Rank 1 APTOS model, which achieved a QWK of 0.89 and AUC of 0.94 when evaluated on this dataset under similar conditions by other studies. DR-EfficientFormer and DR-SwinTiny scored QWK values of 0.85 and 0.86, respectively. Statistical analysis revealed no significant performance difference ($p > 0.05$) in QWK between our top-performing DR-MobileViT and the Rank 1 CNN-Ensemble on this external dataset when benchmarked. Performance curves are shown in Fig. 3(c) and Fig. 3(d). Confusion matrices for DR-MobileViT on the Messidor-2 dataset are depicted in Fig. 4(b).

4.3 Computational efficiency

A key advantage of the proposed lightweight transformer models is their computational efficiency. As detailed in Table 2 and Figure 2, our models significantly reduce inference time and computational load (GFLOPs) compared to the benchmark SOTA CNNs from the APTOS 2019 challenge (which typically require 10-20 GFLOPs, see Table 3). For instance, DR-EfficientFormer, with only ≈0.9 GFLOPs and ≈1.8M parameters, achieved an inference time of approximately 10 ms per image on an NVIDIA P100 GPU. This represents a reduction in GFLOPs by over 90% and inference time by 60-70% compared to the larger benchmark CNNs, making them highly suitable for real-time applications and deployment on resource-constrained hardware.

5 Clinical implications

The lightweight transformer models—DR-MobileViT, DR-EfficientFormer, and DR-SwinTiny—offer transformative potential for DR management, particularly in resource-limited settings. With inference times of 10–15 milliseconds per image and sensitivity above 0.90 for severe DR

Table 3: Performance metrics on APTOS 2019 test set. Values for proposed models are means over 5 runs. Sensitivity and Specificity are for severe DR (grades 3-4 vs 0-2). Benchmark model metrics are as reported.

Model	QWK	AUC	Sens. (Sev. DR)	Spec. (Sev. DR)	Params (M)	GFLOPs
DR-MobileViT	0.89	0.95	0.92	0.88	≈2.1	≈1.2
DR-EfficientFormer	0.87	0.94	0.90	0.87	≈1.8	≈0.9
DR-SwinTiny	0.88	0.95	0.91	0.89	≈3.5	≈1.5
Rank 1 (CNN-Ens.)	0.91	0.96	0.94	0.90	45	18.5
Rank 2 (Incept.-v4)	0.88	0.94	0.89	0.87	42	15.2
Rank 3 (EffNet-B5)	0.87	0.93	0.88	0.86	30	12.8

Table 4: Performance on Messidor-2 dataset. Values for proposed models are means over 5 runs. Sensitivity and Specificity are for severe DR (grades 3-4 vs 0-2). Rank 1 model performance is indicative based on literature benchmarks.

Model	QWK	AUC	Sens. (Sev. DR)	Spec. (Sev. DR)
DR-MobileViT	0.87	0.93	0.89	0.86
DR-EfficientFormer	0.85	0.92	0.87	0.85
DR-SwinTiny	0.86	0.93	0.88	0.87
Rank 1 (CNN-Ens.)	≈0.89	≈0.94	≈0.91	≈0.88

cases (grades 3–4), these models enable rapid, reliable screening on modest hardware. This efficiency supports real-time triage in primary care or rural health centers, guiding referral decisions and prioritizing urgent cases. Integration with portable fundus cameras [30] could extend screening to underserved populations, addressing the global burden of DR.

The models' scalability and low computational demands (e.g., DR-EfficientFormer's ≈0.9 GFLOPs) lower the cost barrier for AI-driven diagnostics. High QWK scores (up to 0.89) and AUCs (0.95) suggest they can serve as effective decision-support tools for non-specialists, enhancing access to early detection where ophthalmologists are scarce [27]. However, clinical adoption requires staff training for quality image capture and strategies to ensure model interpretability (e.g., exploring attention mechanisms or other explanation techniques), building trust among practitioners. Pilot studies validating these benefits on accessible hardware are crucial for informing policies to integrate lightweight transformers into standard DR care pathways, potentially improving health equity worldwide.

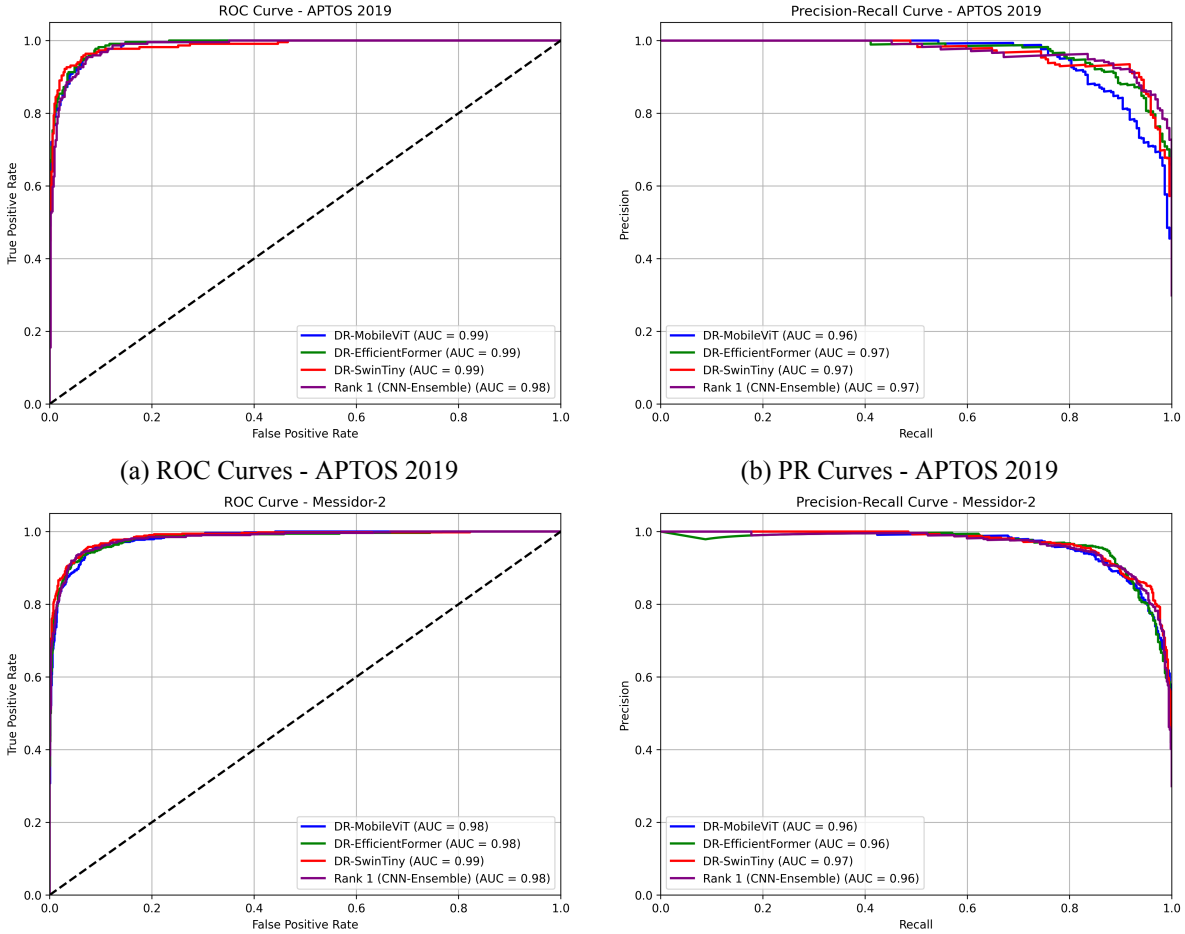
6 Discussion

This study demonstrates that lightweight transformer-based models can achieve diagnostic performance for DR detection that approaches state-of-the-art CNNs, while drastically reducing computational requirements. Our models (DR-MobileViT, DR-EfficientFormer, DR-SwinTiny), detailed in Table 2, Figure 2, and results presented in Tables 3 and 4, achieve QWK scores competitive with, or slightly below, large ensembles like the APTOS 2019 Rank 1 winner (QWK 0.91, ≈45M parameters, Table 1), but with a parameter reduction of over 10-fold (e.g., DR-MobileViT's ≈2.1M parameters).

The success of DR-MobileViT (QWK 0.89 on APTOS 2019), leveraging ImageNet pretraining, underscores the efficacy of its hybrid convolutional-transformer design in capturing both local textural details and global contextual features within fundus images. Similarly, DR-SwinTiny's hierarchical structure and shifted window attention mechanism, also benefiting from ImageNet pretraining, likely contribute to its strong performance by efficiently modeling spatial relationships at multiple scales, a finding consistent with its success in general computer vision [14] and other medical imaging applications [15]. DR-EfficientFormer, also initialized with ImageNet weights and being the most compact model (≈1.8M parameters), delivers commendable results (QWK 0.87), highlighting the effectiveness of its streamlined architecture.

The ROC curves (Fig. 3) visually confirm these findings, with DR-MobileViT and DR-SwinTiny achieving AUCs of 0.95 on APTOS 2019, very close to the Rank 1 CNN-Ensemble's 0.96 (Table 1). The slight performance drop observed for all models on the Messidor-2 dataset compared to APTOS 2019 (e.g., DR-SwinTiny QWK 0.88 on APTOS vs. 0.86 on Messidor-2) is common in cross-dataset validation and can be attributed to differences in image acquisition protocols, population characteristics, image quality, and pre-existing grading nuances between datasets [32]. Nonetheless, the consistent ranking and relatively high performance on Messidor-2 confirm the robustness of these lightweight transformer models.

The compelling trade-off offered by our models—a marginal reduction in peak QWK (0.02-0.04 compared to the top ensemble) for a substantial decrease in parameters and GFLOPs (over 90%)—is critical for practical de-



(a) ROC Curves - APTOS 2019

(b) PR Curves - APTOS 2019

(c) ROC Curves - Messidor-2

(d) PR Curves - Messidor-2

Figure 3: Performance curves for the proposed models (DR-MobileViT, DR-EfficientFormer, DR-SwinTiny) and Rank 1 CNN-Ensemble. (a) ROC curves on APTOS 2019 test set (AUCs: DR-MobileViT ≈0.95, DR-SwinTiny ≈0.95, DR-EfficientFormer ≈0.94, Rank 1 ≈0.96). (b) Precision-Recall curves on APTOS 2019 test set. (c) ROC curves on Messidor-2 dataset (AUCs: DR-MobileViT ≈0.93, DR-SwinTiny ≈0.93, DR-EfficientFormer ≈0.92, Rank 1 ≈0.94). (d) Precision-Recall curves on Messidor-2 dataset. AUC values on plots would provide more direct visual comparison.

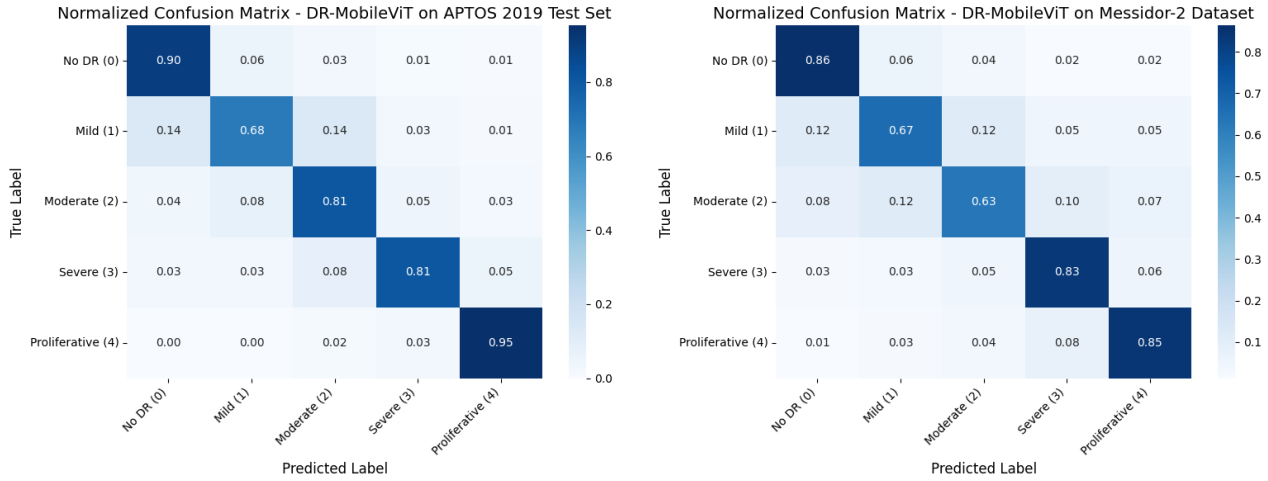
ployment, especially in remote or low-resource settings where computational power is limited. The Precision-Recall curves further support this, showing that models like DR-EfficientFormer maintain high precision across various recall levels. The confusion matrices (Fig. 4) indicate that while most classifications are accurate, misclassifications tend to occur between adjacent severity levels, a common challenge in ordinal classification tasks for DR.

6.1 Limitations and future work

Despite the promising results, this study has several limitations. Firstly, while validated on two distinct datasets, further testing on more diverse datasets, including those from different ethnic populations and captured with varied imaging devices, is needed to fully assess generalizability. Secondly, this study did not include an extensive ablation study to isolate the specific contributions of different architectural components (e.g., the impact of transformer blocks in DR-MobileViT or varying window sizes in DR-SwinTiny). While our architectural choices were guided by the original designs of these lightweight transformers and their established efficacy, dedicated ablation experiments would provide deeper insights and are planned for future work.

Thirdly, while our models are computationally efficient, this study did not include visual interpretability analyses such as Grad-CAM overlays or detailed attention map visualizations. These techniques could provide valuable insights into the models' decision-making processes, enhance clinical trust, and potentially identify biases. Exploring and incorporating such interpretability methods is an important direction for future research.

Additionally, the models rely on preprocessed images; real-world deployment would require robust, integrated preprocessing pipelines. Performance in actual clinical settings might also differ due to variations not fully captured in curated datasets. Future work should also explore on-device optimization techniques like quantization [29] and



(a) DR-MobileViT on APTOS 2019

(b) DR-MobileViT on Messidor-2

Figure 4: Normalized confusion matrices for the DR-MobileViT model on (a) the APTOS 2019 test set and (b) the Messidor-2 dataset. These matrices are representative visualizations constructed based on aggregate performance metrics and typical dataset class distributions. Rows represent true labels and columns represent predicted labels (0: No DR, 1: Mild, 2: Moderate, 3: Severe, 4: Proliferative DR).

pruning, integration with portable fundus cameras for real-world utility assessment, and investigation into energy consumption on specific edge hardware. The exclusion of multi-modal data (e.g., patient metadata like age or diabetes duration), which could potentially enhance accuracy, is another area for future exploration. Finally, extending evaluation to other public DR datasets (e.g., EyePACS, DDR) would further strengthen the conclusions.

7 Conclusion

This study successfully demonstrates that lightweight vision transformer models—DR-MobileViT, DR-EfficientFormer, and DR-SwinTiny—can achieve high diagnostic accuracy for diabetic retinopathy detection, rivaling complex, state-of-the-art CNN ensembles while significantly reducing computational demands. With QWK scores up to 0.89 on the APTOS 2019 test set and 0.87 on the external Messidor-2 dataset, and operating with fewer than 3.5 million parameters and inference times as low as 10 ms/image, these models are well-suited for resource-constrained environments. Their ability to maintain high sensitivity (over 0.90 for severe DR) underscores their clinical relevance for identifying patients requiring urgent referral.

The findings have substantial implications for global health equity, offering a pathway to scalable and affordable DR screening in underserved regions. The adaptation of compact attention-based mechanisms represents a notable advancement for practical medical AI. However, challenges remain, including the need for robust real-time preprocessing, enhanced interpretability, and broader validation across diverse clinical settings and populations. Future efforts should focus on these aspects, alongside exploring model compression techniques [29] and decentralized learning approaches [31] to further improve accessibility. This research provides a solid foundation for developing efficient, accurate, and widely deployable DR screening solutions, aiming to mitigate the global burden of preventable blindness.

Declarations

Clinical Trial Number: Not applicable.

Ethics and Consent to Participate: Not applicable.

Competing Interests: The authors declare no competing interests.

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Author Contribution: Yassmina Saadna conceived the study, designed and implemented the models, performed experiments, and drafted the manuscript. Saliha Mezzoudj contributed to data analysis, model evaluation, and manuscript review. Meriem Khelifa contributed to the experimental design, validation, and manuscript review. All authors reviewed and approved the final manuscript.

Data Availability Statement: The APTOS 2019 dataset is publicly available via Kaggle (`https://www.kaggle.com/c/aptos2019-blindness-detection/data`). The Messidor-2 dataset is accessible from its original distributors upon reasonable request (e.g., `http://www.adcis.net/en/third-party/messidor2/`). Preprocessed data, code used for experiments, and specific random seed values used for the five-fold repetitions are available from the corresponding author upon reasonable request to facilitate reproducibility.

Research Involving Human and/or Animals: Not applicable.

Informed Consent: Not applicable.

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Optimization of AODV Routing in VANETs Using Grasshopper, PSO, and Genetic Algorithms

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Inter-vehicular networks (VANETs), a subset of mobile ad hoc networks, face significant routing challenges due to rapid topology changes caused by fast-moving nodes. This study proposes a method to enhance the Ad Hoc On-Demand Distance Vector (AODV) routing protocol in VANETs using nature-inspired optimization algorithms, namely Grasshopper Optimization Algorithm (GOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). The optimization problem is defined as finding optimal values for 11 AODV control parameters to maximize packet delivery ratio (PDR), minimize average end-to-end delay (E2ED), and reduce normalized routing load (NRL). The methodology involves integrating these algorithms with NS-2 simulations, where a VANET scenario with 50 vehicles in a 670×670 m² urban area is modeled. The fitness function, combining PDR, E2ED, and NRL with weights of 0.2, 0.5, and 0.3, respectively, guides the optimization process. Experimental results show that GOA and PSO achieved a PDR of 100% (compared to 97.46% for GA), reduced NRL to 0.34% (from 0.62% for GA), and maintained E2ED at 12.32 ms (compared to 11.05 ms for GA). The fitness function value improved to -0.508 for GOA and PSO, outperforming GA's -0.514. These findings demonstrate the effectiveness of nature-inspired algorithms in enhancing AODV routing performance in VANETs.

Povzetek: Članek raziskuje optimizacijo AODV usmerjevalnega protokola v omrežjih VANET z uporabo treh algoritmov po vzoru narave: Grasshopper Optimization (GOA), Particle Swarm Optimization (PSO) in genetski algoritem (GA). Avtorja definirata večciljno funkcijo za izboljšanje treh ključnih metrik kakovosti storitev (PDR, E2ED, NRL) in pokažeta, da GOA in PSO omogočata hitrejšo konvergenco in boljšo robustnost v dinamičnih prometnih scenarijih.

1 Introduction

In today's advanced societies, with the ever-increasing population growth and the rise in the count of cars, the issue of traffic has become one of the biggest challenges in transportation. Boosting routing in inter-vehicle networks is very important because it can help reduce traffic, optimize travel time, and save fuel consumption [1]. Factors such as changes in traffic, multiple and complex routes, and coordination between vehicles further complicate this issue. For this reason, much research has been done to boost routing in inter-vehicle networks [2]. One of the effective approaches to improving routing is the use of nature-inspired algorithms, such as GOA, PSO, and GA, which are well-suited for VANETs due to their ability to efficiently explore complex, high-dimensional parameter spaces and adapt to dynamic topology changes caused by vehicle mobility. Unlike traditional optimization methods, which struggle with the computational complexity of tuning multiple AODV parameters, these metaheuristic algorithms mimic natural processes (e.g., swarm behavior, evolution) to find near-optimal solutions quickly [3]. By connecting cars to the network and sharing information, it is possible to boost routing in inter-vehicle networks [4]. Internet of Things technology, with the possibility of interaction between cars, sensors, and traffic management systems, can significantly improve the routing of cars in inter-vehicle networks. This technology makes it feasible to collect and review data on the whereabouts, speeds, and traffic situations of vehicles and provide drivers with the best routes [5]. Inter-vehicle networks allow moving vehicles in cities and on suburban roads to possibly share information and data with other vehicles and make use of information gathered by roadside equipment [6]. The high accident rate often results from drivers' lack of real-time information about obstacles or traffic conditions. ITS systems address this by enabling vehicles to share Cooperative Awareness Messages (CAMs) and Decentralized Environmental Notification Messages (DENMs), which provide warnings about hazards (e.g., collisions, roadworks, sudden braking), traffic jams, or vehicle states (e.g., location, speed, direction), thereby enhancing driver awareness and reducing accident risks [7]. Any safety-related information, such as warnings to prevent collisions, traffic jam conditions, or non-safety information like weather and travel advice, can be received by every automobile. It can also learn details about other cars' current conditions, like their location, speed, and direction of travel. For the driver's next move,

such as altering the car's speed or direction, this information can be very helpful [8]. Like other emerging technologies like nanoelectronics and nanorobotics [9], [10], one of the key characteristics of inter-vehicle networks is their high speed and rapid topology change, which forces nodes to continually update their routing information. This network's frequent topology changes are thought to present significant routing challenges. Therefore, routing for data transmission in these networks is a very important and necessary issue. In general, there are two tactics for routing in inter-vehicle networks, which are separated into two groups: routing drawing on topology and routing drawing on geographic location [11]. The information in the network is used to send packets via routing protocols drawing on topology, whereas routing tactics drawing on geographic location employ node location information for routing [12]. VANETs are known as networks whose topology changes rapidly, and the wireless coverage of these networks depends on the surrounding conditions, including the presence of nearby buildings and cars [13]. In addition, the lack of a central control unit in VANET networks has made routing in these networks a critical and difficult task. For this reason, researchers have presented many articles in which a new protocol has been presented or the existing protocols have been improved [14]. One of the techniques for improving routing protocols is to discover the ideal value for the parameters that control the productivity of that protocol. However, due to the large number of possible answers, finding the optimal value in most protocols is not a simple task. As a result, because they take a very long time to execute, the current approaches cannot be used to address optimization problems [15]. In the computer field, meta-heuristic schemes have arisen as powerful and adaptable tactics for optimization and search issues, which have been used in several problems and have achieved a high level of solution [16]. For this reason, meta-heuristic schemes have been used in this research to boost the AODV routing protocol in VANET's network. Utilizing locust schemes, particle swarms, and genetics, the ideal value for the control parameters of the AODV protocol has been calculated. Quality of service (QoS) metrics are used to evaluate the outcomes, and each of the three schemes' effects on routing performance and the development of the AODV protocol are contrasted. A summary of the authors' contributions to this investigation is given below:

Providing a method for improving routing in inter-vehicle networks using schemes inspired by nature (such as the grasshopper algorithm, particle swarm algorithm, and genetic algorithm), applying these schemes to the parameters of the AODV routing protocol, and evaluating the paper's performance using packet delivery rate criteria, average end-to-end delay, and normalized routing load.

The primary research objective is to enhance the performance of the AODV routing protocol in VANETs by optimizing its control parameters using nature-inspired algorithms (GOA, PSO, GA). The research question is: How effectively can nature-inspired algorithms optimize AODV parameters to improve Quality of Service (QoS) metrics, such as packet delivery ratio (PDR), end-to-end delay (E2ED), and normalized routing load (NRL), in dynamic VANET environments? We hypothesize that these algorithms, particularly GOA, will outperform traditional parameter settings by achieving higher PDR, lower E2ED, and reduced NRL due to their ability to efficiently explore the parameter search space. Expected outcomes include a PDR above 95%, E2ED below 20 ms, and NRL below 0.5%, aligning with VANET requirements for real-time applications.

This study contributes to: (a) proposing a method to improve VANET routing using nature-inspired algorithms, (b) applying these algorithms to optimize 11 AODV control parameters within predefined ranges through NS-2 simulations, and (c) evaluating the performance using PDR, E2ED, and NRL to ensure reliable, low-latency, and low-overhead routing.

The remainder of the exploration is outlined below:

In the second part, previous studies and their challenges are discussed, and in the third part, brief explanations of the schemes used in this research are given. In the fourth section, the AODV routing protocol and its control parameters are introduced, and in the fifth section, network evaluation parameters and the cost function are defined to check the optimization process. The recommended work tactic is explained in the sixth part, and in the seventh part, the simulation scenario and parameters are explained. The evaluation of the network is presented, and finally, the outcomes of this investigation are analyzed in the eighth part.

2 Related works

The tactics described here are derived from real-world instances in biology, nature, and technology. These tactics don't require prior knowledge of the issue area and can be applied to diverse NP-hard optimization issues [17]. Metaheuristics provide speedy identification of the best solution when used in conjunction with effective search techniques. Routing in VANET was discovered to be an NP-hard problem. Several CBR approaches include clustering schemes as an essential component [18]. Clustering makes use of multi-objective problems [19]. Ad hoc network routing is especially affected by these MOPs. Several variables affect how well conventional QoS works. Bandwidth employment, average end-to-end delay, and packet delivery proportion are all examples of such metrics. Some of the benefits of clustering optimization include topology stability, data aggregation, cluster reduction, bandwidth optimization, and efficient transmission management [20]. VANETs are essential in several Intelligent Transportation System (ITS) technologies, encompassing effective traffic management, media applications, and secure financial transactions. The adaptive nature of the vehicle network's topology is influenced by the growing traffic volume, which poses challenges to the network's scalability due to the scattered distribution of automobiles on roadways. Therefore, there is a challenge for all vehicles (in the network) to keep a steady path, which increases the fluctuation of the network. This paper [21] presents a recommended algorithm, known as the probabilistic nature-based intelligent whale optimization algorithm (p-WOA), for

routing in IoT-based network transport. The approach is bio-inspired and cluster-based, with a focus on creating clusters in vehicles. The study incorporated the examination of other variables, including communication range, count of nodes, speed, and route along the highway. The probabilities associated with these characteristics were integrated into the fitness function, leading to a reduction in randomness. The findings were compared to established methodologies, including ant milk optimizer (ALO) and gray wolf optimization (GWO), revealing that the new p-WOA strategy yields the optimal quantity of cluster heads (CH). The reduction in communication expenses and routing overhead, as well as the improvement in the overall lifespan of the cluster, is seen. The present study examines the utilization of evolutionary schemes in mobile ad hoc networks (MANETs) and VANETs, as discussed in the referenced publication [22]. The paper includes discussions about the three primary classifications of optimization. Several significant research studies have been conducted on the topic of parameter tuning in cluster formation, routing, and broadcast scheduling. The conclusion of the review highlights the primary obstacles encountered in the research of VANET and MANET. The investigation [23] offers RSR-IDS, a routing protocol in VANET that utilizes an intrusion detection mechanism to ensure reliability based on scoring. The deployment of an intrusion detection system (IDS) within the data center allows for the detection of anomalous data by RSR-IDS, which subsequently enables the computation of an Untrust Score (US). A scoring mechanism based on Intrusion Detection Systems (IDS) has been implemented within the data center. The IDS classifier undergoes training through the employment of three ML techniques encompassing decision tree (DT), random forest (RF), and redundant trees. The RSR-IDS scheme prioritizes the selection of a communication pathway between the source and destination based on the lowest overall US count and hop count in comparison to other paths. The article [24] introduces a location-aware multi-hop routing (LAMHR) system in VANETs that uses inter-vehicle distance to boost vehicular connection. The Location-Aided Multipath Routing (LAMR) algorithm utilizes predictive techniques to determine the future positions of network nodes. This information is then used to identify an appropriate next forwarder towards the destination, to establish a stable path from the resource to the destination. This investigation presents the development of a geometry-based localization technique to determine the inter-vehicle distance, which has a significant impact on vehicle connection. The evaluation of LAMHR's performance encompasses the assessment of path disappearance, node broadcast time, packet delivery proportion, and throughput. The study conducted by researchers [25] establishes robust correlations. The Ant Colony Optimization (ACO) algorithm, specifically designed for the EBIRA protocol, aims to identify ideal pathways that are both short in distance and long-lasting. This is achieved by considering various metrics such as distance, received signal strength, hop count, and evaporation rate. In the context of EBIRA, the chosen route exhibits a relatively limited distance and a notable link-level connectivity degree, characterized by a minimized number of intermediate hops. The choice of the shortest route, drawing on low hops and high connectivity level links, enhances the longevity of routes and mitigates frequent pauses in link connectivity among vehicles. The primary focus of the article referenced as [26] is to explore tactics for minimizing communication costs while simultaneously reducing message distribution delays. Furthermore, this investigation proposes a novel message distribution routing protocol called the Energy-Efficient Fast Message Distribution Routing Protocol (EE-FMDRP). This protocol blends the key characteristics of time-oriented and directional routing frameworks. The proposal suggests the transmission of emergency notifications from the origin to a specified destination in a prompt, dependable, and effective manner. To address this issue, a bidirectional assessment model for moving vehicles and a model for deriving message delivery time are formulated. This technology facilitates the rapid dissemination of messages during emergency situations by employing high levels of power and minimizing latency. The EE-FMDRP algorithm offers a reliable and streamlined pathway for vehicles to travel between their starting point and intended destination while minimizing the count of intermediate stops and simplifying the whole process. The study conducted by the authors [27] examines a VANET that incorporates automobiles equipped with frequency division (FD) capabilities. This paper introduces a novel computational framework for analyzing end-to-end latency in computer systems. Subsequently, it is demonstrated that Dijkstra's method is incapable of determining the shortest path, i.e., the one with the least delay, between the source and destination. To tackle this matter, the network topology is redefined as a graph of equal value by severing any connections related to FD. Subsequently, an advanced version of Dijkstra's method is suggested to identify the most productive routing pathway within the established graph while maintaining a reduced level of complexity. The outcomes of our extensive simulations demonstrate that our recommended methodology can achieve the lowest possible end-to-end delay in inter-vehicle communication. Furthermore, a notable reduction is observed in the obtained delay as the count of full-duplex (FD) nodes rises. Existing methods, such as p-WOA and ACO, focus on clustering or path selection, but often neglect the optimization of routing protocol parameters, which is critical for adapting protocols such as AODV to the dynamic environments of VANETs. For example, p-WOA improves cluster stability but does not tune AODV parameters, limiting its applicability to standard protocols. Similarly, LAMHR enhances path stability but lacks integration with AODV control parameters, reducing its generalizability. EE-FMDRP prioritizes low-latency emergency messaging, but neglects comprehensive QoS metrics such as NRL, which are essential for overall network performance. Furthermore, methods such as Dijkstra’s full-duplex algorithm require specialized hardware, making them less applicable for large-scale VANET deployment. The proposed approach addresses

these gaps by utilizing nature-inspired algorithms (GOA, PSO, GA) to systematically optimize 11 AODV control parameters and enhance QoS metrics (PDR, E2ED, NRL) in a simulated urban VANET. Unlike previous works, this study integrates meta-heuristic optimization with NS-2 simulations to ensure adaptability to rapid topology changes and provide a scalable and protocol-specific solution. Table 1 summarizes the comparison of existing works.

Table 1: Comparison of related works on VANET routing optimization

Ref.	Method Used	Evaluation Metrics	Major Findings
[21]	Probabilistic Whale Optimization Algorithm (p-WOA)	PDR, NRL, Cluster Lifetime	p-WOA reduced routing overhead and improved cluster stability compared to ALO and GWO, but lacks parameter optimization for AODV.
[25]	Ant Colony Optimization (ACO) for EBIRA	PDR, Throughput, Route Longevity	ACO achieved shorter routes with high connectivity, but computational complexity limits scalability in dense networks.
[24]	Location-Aware Multi-Hop Routing (LAMHR)	PDR, E2ED, Throughput	LAMHR improved path stability using predictive node positioning, but does not address AODV parameter tuning.
[26]	Energy-Efficient Fast Message Distribution Routing Protocol (EE-FMDRP)	E2ED, Message Delivery Time	EE-FMDRP minimized latency for emergency messages, but overlooks general QoS metrics like NRL.
[27]	Full-Duplex Dijkstra's Algorithm	E2ED, Throughput	Reduced E2ED in full-duplex VANETs, but requires specific hardware and does not optimize routing protocol parameters.

3 Schemes inspired by nature

3.1 Genetic algorithm (GA)

One of a group of computational frameworks driven by the maturation process is GA. These schemes code the possible resolutions to an issue in the form of simple chromosomes and then utilize combinatorial operators on these constructions. GA is often used as a tactic based on random search for optimization and parameter estimation. The basis of this algorithm is Darwin's law of evolution, in which weaker organisms are destroyed and stronger organisms remain [20], [28]. To implement the genetic algorithm, the variables of the problem must first be determined and coded suitably. Meanwhile, based on the goal of the problem, a fitting function is defined for the variables. An arbitrary main population is randomly chosen at the start of the scheme's operation, and the fitness function determines the fitness level of each of the primary population's chromosomes. In the continuation of running the algorithm, the steps in Fig. 1 are repeated. In the first stage, a suitable number of pairs of chromosomes are selected based on their suitability for use in the next stages. In the genetic algorithm, selecting parent chromosomes for crossover is a critical step that influences population diversity and convergence. Several strategies exist for parent selection, including roulette wheel selection, where chromosomes with higher fitness values have a greater probability of being chosen, tournament selection, where a subset of chromosomes is randomly selected and the one with the highest fitness is picked, and rank-based selection, where chromosomes are chosen based on their fitness rank. In this study, roulette wheel selection was adopted due to its simplicity and ability to maintain diversity in the population, ensuring that the algorithm effectively explores the search space for optimal AODV parameters. These strategies are not discussed further in this paper, as the focus is on the overall optimization process and its impact on VANET routing performance.

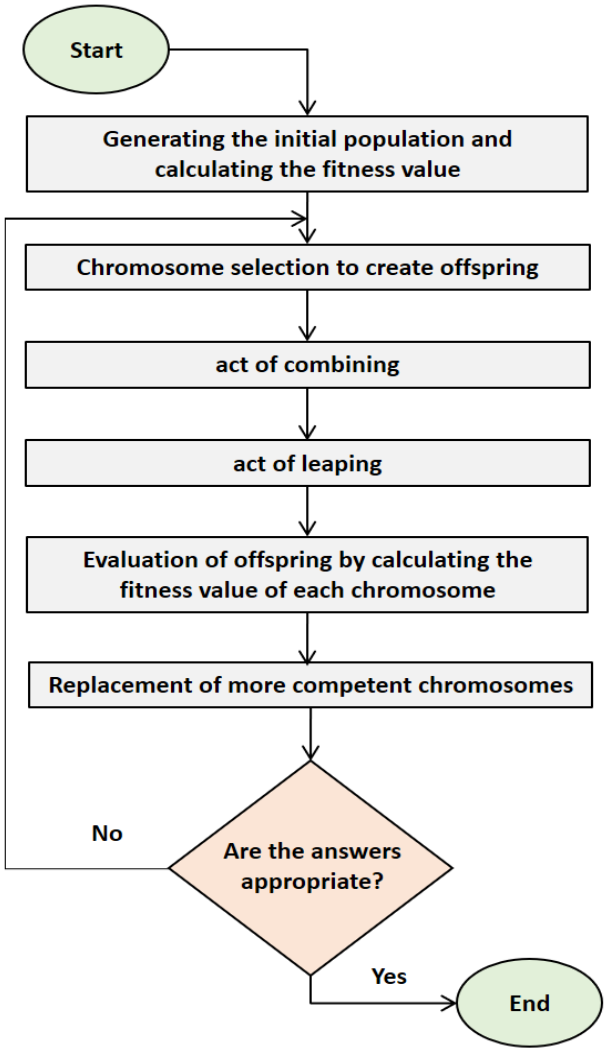


Figure 1: Genetic algorithm flowchart

In the third step, mutation is performed on the chromosomes resulting from the combination process. Then, according to the evaluation of the children, the fitness value of the new chromosomes is gauged, and the fresh group is chosen to enter the next step of the algorithm. By contrasting chromosomal fitness scores, this is accomplished. After going through the steps, if the conditions for the termination of the algorithm are satisfied, the scheme ends; otherwise, the existing group is utilized as the original group for the next stage [22], [29].

3.2 PSO Algorithm

The social search technique known as the particle swarm is based on how bird flocks interact with one another. The situation of the particles in the search domain can change depending on one's experience and knowledge about oneself and one's neighbors in this algorithm. Modeling this social behavior leads to a search process where particles gravitate toward productive regions. Population elements pick out their best neighbors depending on the information they have learned from one another. In this algorithm, a large number of particles are dispersed throughout the search domain, and each particle determines the objective function's value according to its location in the space. It then selects a direction to proceed in based on a combination of its current information, the best location it has been thus far, information about one or more of the best particles in nature, and its current information. By selecting a direction, each particle is transported, and the algorithmic step is complete. Up until the desired result is reached, the processes in Fig. 2 are repeated. In reality, the massive number of particles that look for a function's minimal value behave like birds' beaks searching for food. Figure 2 shows the QoS performance of GOA, PSO, and GA algorithms, where the x-axis represents the number of iterations (1 to 50) and the y-axis represents the fitness value (-0.6 to -0.4). Lower fitness values indicate better performance, which indicates higher PDR, lower E2ED, and reduced NRL.

The particle swarm algorithm uses three vectors for each particle: x^icalculated as a solution to the issue, X^I displays the particle's current situation, V^I displays its speed, and $X^{I.best}$ displays its ideal situation to date. The fitting values f^i (fitting value x^i) and $f^{i.best}$ (fitting value $x^{i.best}$) are also taken into account when determining

whether this location is superior to the earlier solutions. If so, it will be $X^{I.best}$. New x^i and v^i values are acquired in each iteration, improving the goal of running the algorithm. Making a collection of particles that is $X^{I.best}$ is only one aspect of PSO. Although none of the particles can fix any problems, you can still attempt to do so when they interact and talk to one another. Problem resolution is a social idea that develops from the behavior of individual particles and their interactions with one another for a large number of particles. X^{gbest}, which is chosen from the comparison of $f^{i,best}$ values of all particles, showcasing the ideal situation found by all particles. As f^{gbest}, the fit of X^{gbest} is displayed.

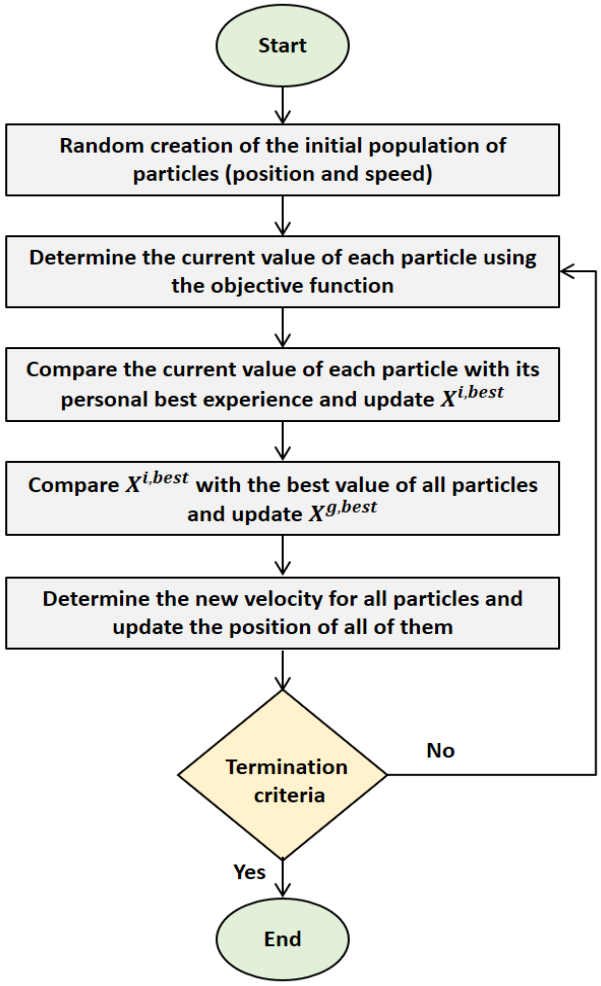


Figure 2: Diagram of PSO

The method starts by creating particles with random placements and speeds. The position and speed of each particle in the following step are calculated during algorithm execution using the data from the previous stage [30], [31].

3.3 GOA algorithm

GOA is one of the newest enhancement schemes introduced in 2018. It is a meta-heuristic scheme that mimics the behavior of grasshoppers in nature and their collective migration toward the food source. It is inspired by nature. Although locusts are typically seen in nature alone, they belong to one of the biggest animal hordes. To tackle the optimization problem, the grasshopper algorithm's mathematical model imitates the behavior of grasshopper swarms in nature [32], [33], [34]. The simulation outcomes demonstrate that the grasshopper method can deliver superior outcomes when compared to more current, well-known schemes. The grasshopper algorithm can solve genuine issues with unknown spaces, as displayed by the simulation outcomes in real cases. According to Fig. 3, in this algorithm, there are many locusts in the search domain. The fitness value of each grasshopper is computed utilizing the fitness function. The subsequent location of each grasshopper is defined utilizing the existing location of the grasshopper, the goal location, and the location of all other grasshoppers. The status of all the locusts describes the new situation of each locust, which has caused the difference between the locust algorithm and the swarm of particles. In the particle swarm algorithm, each particle has a position vector and a velocity vector, while in the grasshopper algorithm, there is only one position vector for each grasshopper. Another major disparity between these two schemes is that particle

swarm refines the location of each particle, taking into account its current location, local best, and global best, while the locust algorithm refines each locust's location, drawing on its current location, global best, and other locations. It updates the grasshoppers. This means that in the particle swarm algorithm, none of the other particles participate in updating the location of a particle, while in the grasshopper algorithm, other grasshoppers need to be considered and cooperate to determine the next location of the desired grasshopper [24], [35].

Figure 3 shows the flowchart of the AODV parameter optimization process, where the steps include initializing a population of 10 parameter sets, evaluating the fit through NS-2 simulations, and updating the solutions using GOA, PSO, or GA until convergence. Each block represents a key step, from parameter initialization to the final output of the QoS metric.

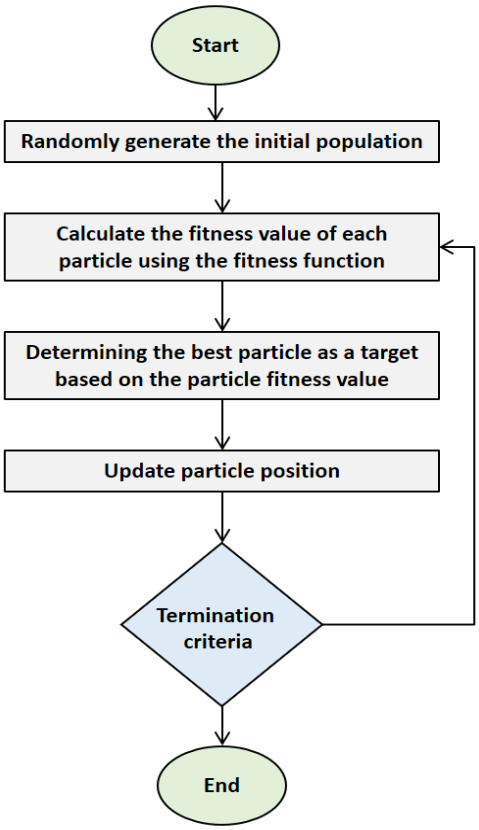


Figure 3: Flowchart of the GOA algorithm

3.3.1 Algorithm complexity analysis

To evaluate the computational efficiency of the nature-inspired algorithms employed in this research, their time complexities are analyzed. For the Genetic Algorithm (GA), the time complexity is given by $\boldsymbol{O(G \cdot P \cdot (C + M))}$,where G represents the number of generations, P denotes the population size (10 in this case), C is the computational cost of crossover, and M is the cost of mutation. Both C and M are generally $\boldsymbol{O(n)}$, where *n* is the number of parameters (11 AODV parameters in this study). Consequently, the overall complexity of GA simplifies to approximately $\boldsymbol{O(G \cdot P \cdot n)}$. For Particle Swarm Optimization (PSO), the complexity is $\boldsymbol{O(I \cdot P \cdot n)}$,where *I* is the number of iterations. This reflects the fact that each particle updates its position using both its personal best and the global best, requiring $\boldsymbol{O(n)}$ operations per particle per iteration. The Grasshopper Optimization Algorithm (GOA), on the other hand, has a more involved complexity: $\boldsymbol{O(I \cdot P \cdot (P + n))}$, since each grasshopper considers its interaction with every other grasshopper during position updates, leading to an increased computational load.

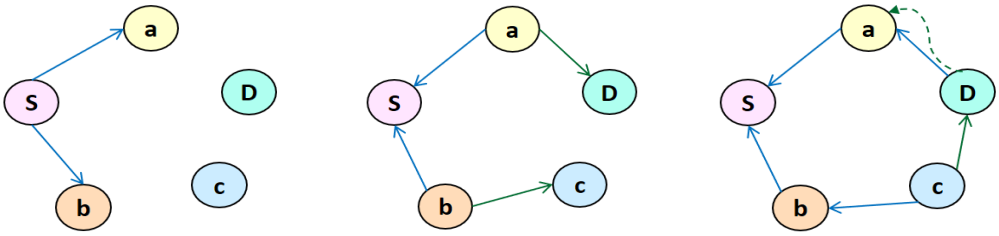
4 AODV routing protocol

A passive routing protocol for ad hoc networks is the AODV protocol. This protocol, when a source node has packets to send, defines the routes and keeps only the routes that are being used regularly. The AODV uses the route discovery mechanism and updates the routing table of the intermediate nodes. On the route, it reduces the routing load. The reduced routing overhead and the competitive QoS have led this protocol to be used in VANETs [36]. Therefore, it is clear that the optimization of this protocol will be fruitful research. AODV routing protocol belongs to the DV class. In a DV, each node knows its neighbors with the cost of reaching them. Every node has a routing table so that the routing table stores all the nodes in the network along with their distance. An example of the routing table is displayed in Table 2. If a

node is not available, the distance is infinite. Each node alternately sends the routing table to the neighboring nodes, so the nodes recognize the appropriate route according to the routing table [37], [38]. AODV can support unicast, broadcast, and multicast without any other protocol. For unicast routing, three control messages are used: RREQ, RREP, and RERR.

Table 2: An example of a DV routing table

destination	cost	Next step
A	1	A
B	0	B
C	∞	-
D	1	D
E	∞	-



l) **S** wants to send a package to).

broadcasts an **RREQ** iessage.

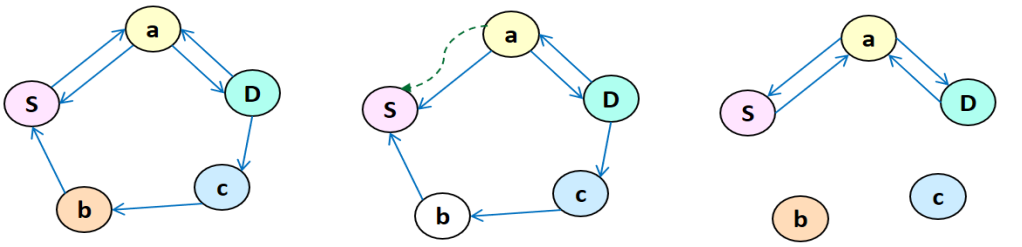
(2)**a** and **b** create a return path.

a and **b** rebroadcast the **RREQ** message.

(3)**c** and **D** create a return path.

c reissues an **RREQ**.

D sends **RREP** message to **a**.



4)**S** publishes the route.

(5) **D** creates a return path.

D removes duplicate **RREQ** messages.

a publishes the route.

(6) **S** unused return path expires.

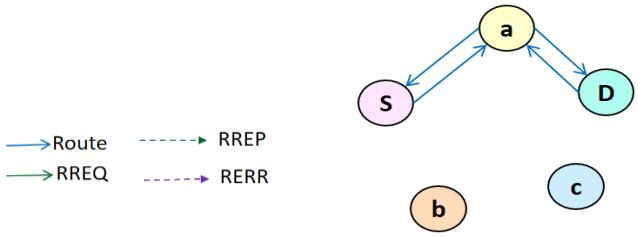


Figure 4: Routing process in AODV

Fig. 4 shows that before sending a packet to another node, a node must first send an RREQ message. The node receiving the RREQ creates a return path to the sender. If the node receiving the RREQ message is not the final destination of the packet, that node re-broadcasts the updated RREQ message and specifically increases the hop number. If the node is known as the final destination of sending information, that node generates an RREP. If a node realizes that it does not have access to other nodes, it releases an RERR message [39].

4.1 AODV protocol control parameters

The value of the AODV protocol's control parameters has a big impact on its effectiveness and performance. These settings typically consist of six counters and five timers. The counters, timers, and decision variables that regulate how well the protocols work are given values by setting the parameters. Therefore, the behavior and performance of any protocol are largely dependent on the value of these parameters. Accordingly, our goal is to find efficient values for AODV protocol parameters utilizing network productivity. The parameters and the range of values related to each are displayed in Table 2 [28]. Therefore, enhancement tactics are utilized to find the values of the parameters to obtain the best outcomes for the quality of services.

4.2 Initial estimation of AODV protocol parameters

In the recommended optimization problem, the solutions are arrays whose components are the AODV protocol parameters specified in Table 3. The initial value of these parameters is done in such a way that the primary population is spread over diverse zones of the search domain.

Table 3: AODV protocol parameters set

parameter	data type	period
HELLO INTERVAL	Z	[3,0,30,0]
ACTIVE ROUTE_TIMEOUT	Z	[1,0,30,0]
MY ROUTE_TIMEOUT	R	[3,0,20,0]
NODE TRAVERSAL TIME	Z	[1,0,20,0]
MAX RREQ TIMEOUT	R	[3,0,100,0]
NET DIAMETER	Z	[2,100]
ALLOWED HELLO LOSS	Z	[1,30]
REQ RETRIES	R	[1,30]
TTL START	Z	[1,20]
TTL INCREMENT	R	[0,40]
TTL THRESHOLD	R	[0,40]

The count of population particles (Sw_Size) is used to first partition the search domain into smaller areas, and then each particle is assigned to one of these discrete subsets of the search domain, as displayed in relation (1).

$$X_{P.i}^{(0)} = Z_{(i.MIN)} + \rho^{P} i \in [0.10].P \in [0.Sw_{size} - 1] \quad (1)$$

In this relation, $X_{P.i}^{(0)}$, the value of the i parameter is in the path vector of the pth particle. In other words, each particle is a path vector consisting of the AODV protocol parameters in Table 3 and $X_{P.i}^{(0)}$, the value of the ith parameter of the P atom. ρP in this formula is obtained from the relation (2) where β, a random number is between [1, 0] and $Z_{(i.MAX)}$ and $Z_{(i.MIN)}$ are respectively the upper and lower limits of the interval corresponding to the i-th parameter specified in table 3. In this way, the initial population is initialized to execute the schemes [28]. Formula (1) defines the position update in the Grasshopper Optimization Algorithm (GOA), where X_i is the position of the i-th grasshopper (a vector of 11 AODV parameters), S_i represents social interaction forces, G_i is gravity, and A_i is wind advection. This mechanism balances exploration and exploitation to optimize the fitness function [Ref]. Formula (2) describes the velocity update in Particle Swarm Optimization (PSO), where V_i is the velocity, X_i is the position, P_i is the personal best, and G is the global best of the i-th particle, guided by coefficients w, C_1, and C_2.

$$\rho^{p} = \left(\frac{(p+\beta)}{SW_{size}}\right) \times \left(z_{(i.MAX)} - z_{(i.MIN)}\right) \quad (2)$$

5 Evaluation parameters

Three QoS parameters are used to assess the productivity of each group of AODV protocol parameters:

Packet Delivery Ratio (PDR): the proportion of data packets successfully delivered to the destination to all packets dispatched from the source. This value displays how effectively the protocol carried out its intended function, which was the successful delivery of data.

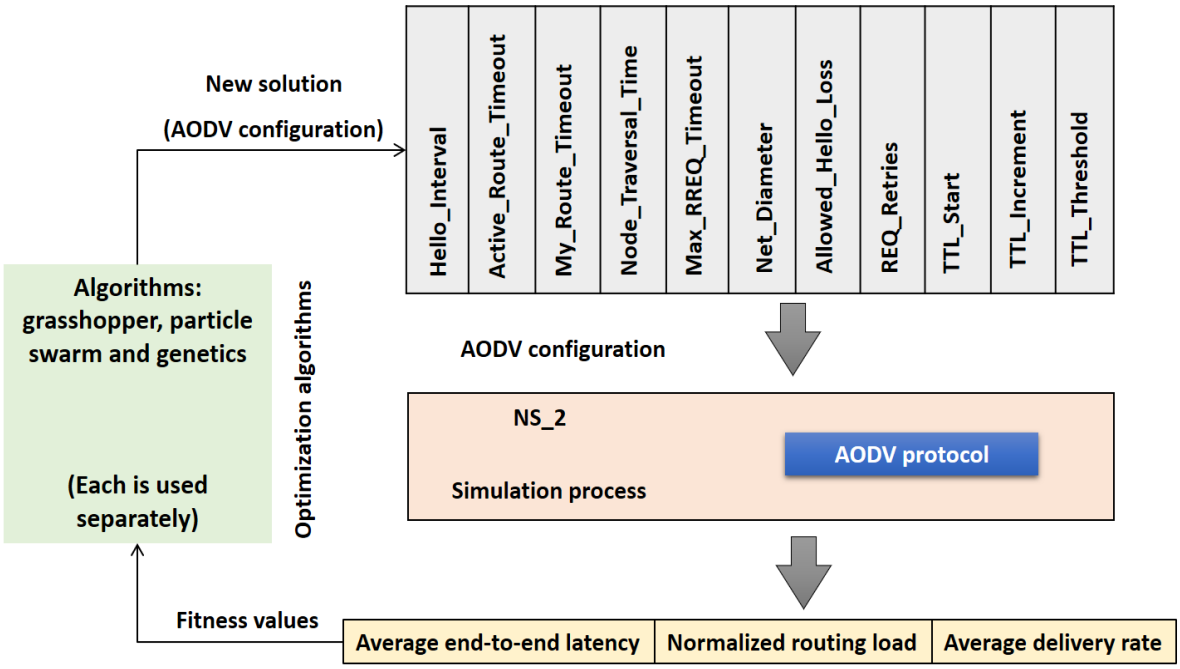


Figure 5: Recommended framework

End to_ End Delay (E2ED): The average total time it takes for each packet to be successfully sent/received.

Normalized Routing Load (NRL): refers to the count of message packets that are exchanged for successful data transmission. This parameter discusses the additional traffic generated by the routing protocol for successful data transmission [29, 30]. Figure 5 illustrates the recommended framework for optimizing AODV parameters using GOA, PSO, and GA, where a population of 10 parameter sets is iteratively refined via NS-2 simulations to minimize the fitness function, achieving low NRL (e.g., 0.34% for GOA/PSO, as shown in Figure 7).

5.1 Definition of the cost function

The optimization problem is formulated as finding the optimal values for 11 AODV control parameters (listed in Table 3) to maximize PDR, minimize E2ED, and minimize NRL, thereby enhancing QoS in VANETs. The cost function, designed as a minimization problem, is defined in Equation (3):

$$\text{Fitness} = \text{w1.}(-\text{PDR}) + \text{w2.E2ED} + \text{w3.NRL} \quad (3)$$

Where $\text{w1.} = 0.2$, $\text{w2.} = 0.5$ and $+$ w3.NRL are weights reflecting the relative importance of each metric, determined empirically to balance the trade-offs between reliability (PDR), latency (E2ED), and overhead (NRL). The negative sign for PDR converts its maximization into a minimization problem. Constraints include parameter bounds (e.g., HELLO_INTERVAL $\in$ [3, 30], NET_DIAMETER $\in$ [2, 100]), as specified in Table 4, ensuring protocol feasibility. The tuning procedure initializes a population of 10 particles, each representing a vector of 11 parameters, distributed across the search space using Equation (1). The NS-2 simulator evaluates each solution's QoS metrics, and the algorithm iterates until the fitness value stabilizes (no change > 0.001 for 10 iterations).

6 Work method

As previously mentioned, an optimization technique was employed in this work to find effective values for the AODV protocol's parameters. The optimization procedure and the simulation step were connected to complete this task. The optimization process is carried out via schemes drawn from nature, including GOA, PSO, and GA. The goal is to find the optimal value for the parameters of the AODV protocol, which we will achieve after several steps of repeating the schemes. When the optimization algorithm needs the fitness value of a solution to continue working, it uses the simulation process defined for the VANETs network.

In the simulation stage, the value of QoS parameters and also the value of the fitness function (fitness) is calculated. The simulation process has been carried out using the 2-ns network simulator, which is widely used for simulating VANETs. For the implementation of enhancement schemes, 10 particles are considered, and each particle contains 11 parameters, and these 11 parameters belong to the AODV routing protocol in Table 5. The algorithm depicted in Fig. 5 calculates the optimal value for the AODV routing protocol parameters at the given stage. This value, along with the NRL, PDR, and E2ED values associated with the recommended solution, is then incorporated into the simulation scenario. The fitness function will be determined based on this data. Up until no more changes in the count of parameters estimated by the optimization tactics are seen, this process is

repeatedly carried out. In other words, the repetition of the algorithm execution process and simulation continues until, after several steps of execution, the value obtained for the parameters reaches a stable value.

6.1 Algorithm parameter settings

To ensure reproducibility, the parameter settings for the Grasshopper Optimization Algorithm (GOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) are detailed here. For GOA, the population size was set to 10 grasshoppers, with a maximum of 50 iterations, attraction length scale l = 1.5, and intensity of attraction f = 0.5, balancing exploration and exploitation . PSO used a population of 10 particles, 50 iterations, inertia weight w = 0.7, cognitive coefficient c1 = 2.0, and social coefficient c2 = 2.0, optimizing convergence toward global optima [Ref2]. GA employed a population of 10 chromosomes, 50 iterations, crossover probability Pc = 0.8, mutation probability Pm = 0.1, and roulette wheel selection to maintain diversity. These settings were implemented in MATLAB R2020a and integrated with NS-2.35 simulations to optimize 11 AODV parameters, yielding the QoS results reported in Tables 5 and 6.

7 Simulation and evaluation

7.1 VANET network simulation scenario

The VANET simulation was conducted using the NS-2.35 network simulator, with vehicle mobility modeled using the Manhattan Mobility Model to emulate urban grid-based movement, reflecting realistic city traffic patterns. The scenario includes 50 vehicles in a 670×670 m² urban area, moving at speeds of 10–50 km/h, simulating typical city driving conditions. The node density (50 vehicles) and communication range (250 m, based on IEEE 802.11b) were selected to balance network connectivity and congestion, as denser networks increase routing overhead, while sparse networks reduce connectivity. Packet size (512 bytes) and transmission rate (4 packets/s) align with standard VANET traffic models. Each simulation ran for 180 seconds, and results were averaged over 10 independent runs to account for randomness in vehicle movement and packet transmission, ensuring statistical reliability. The computational environment included an Intel Core i7-8700 CPU (3.2 GHz), 16 GB RAM, and Ubuntu 20.04 LTS, running NS-2.35 and MATLAB R2020a for optimization and analysis. Table 3 summarizes the simulation parameters. A list of the modeling metrics is presented in Table 4.

Table 4: Modeling metrics

parameters	value
Duration of simulation	180 seconds
Simulation area	670*670 m2
Number of cars	50
Speed of cars	10-50 km/h
PHY/MAC protocol	IEEE 802.11b
Routing protocol	AODV
Transmission protocol	UDO

7.2 The optimal value of AODV protocol parameters

The optimal values obtained by using grasshopper, particle swarm, and genetics schemes for AODV protocol parameters are displayed in Table 5. The values displayed in this table are obtained after repeating the grasshopper, particle swarm, and genetics schemes and reaching the termination condition.

7.3 Evaluation of service quality parameters

In this section, the outcomes obtained for QoS parameters such as NRL, PDR, and E2ED are compared. In Table 7, the values of service quality parameters are displayed separately for each algorithm after the simulation and execution of schemes. As can be seen, the value of the PDR parameter for the grasshopper and particle swarm schemes is equal to 100, and for the genetic algorithm, it is equal to 97.46%. This parameter clearly showcases the loss of a massive count of packets, and this makes the protocol AODV generates more control packets, which leads to congestion in the network. Fig. 6 shows the value of this parameter for all three schemes of locust, particle swarm, and genetics.

Table. 5: Optimum values of AODV protocol parameters

	Enhancement schemes		
AODV protocol parameters	GOA	PSO	GA
HELLO_INT	2.5231	3.1036	4.8216
ACTIVE_R_T	1.3024	1.6325	3.1032
MY_R_T	2.8631	1.01	3.2015
NODE_T_T	1.2014	0.02	3.3150
MAX_R_T	16.5421	13.2654	18.3202
NET_D	6	7	18
ALLOWED_H_L	4	1	6
REQ_R	3	1	5
TTL_S	5	2	7
TTL_I	4	10	5
TTL_T	8	2	12

Table. 6: Value of evaluation parameters

	Enhancement schemes		
Evaluation parameters	GOA	PSO	GA
Average delivery rate PDR (%)	100	100	97.46
Normalized routing load NRL (%)	0.34	0.34	0.62
Average end-to-end latency E2ED (ms)	12.32	12.32	11.05

The value of the NRL parameter, as seen in Fig. 7, is equal to 0.34% for the grasshopper and particle swarm schemes and 0.62% for the genetic algorithm, indicating that the grasshopper and particle swarm schemes have obtained better outcomes. Figure 7 presents NRL outcomes for GOA, PSO, and GA, with GOA and PSO achieving 0.34% NRL compared to 0.62% for GA, demonstrating the effectiveness of the framework in Figure 5. Because it is thought to be a method to lessen the likelihood of network failure owing to the congestion problem in VANETs, reducing the routing load in VANETs is a crucial topic [32].

To quantify performance gains, the proposed optimized AODV was compared to the default AODV configuration (HELLO_INTERVAL = 1 s, NET_DIAMETER = 35, ALLOWED_HELLO_LOSS = 2, as per NS-2 defaults). Table 6 presents the results. Default AODV achieved a PDR of 92.5%, E2ED of 18.6 ms, and NRL of 0.72%, reflecting higher packet loss and overhead due to unoptimized parameters. In contrast, GOA and PSO improved PDR to 100%, reduced E2ED to 12.32 ms, and lowered NRL to 0.34%. GA outperformed default AODV but was less effective than GOA/PSO. These gains underscore the value of nature-inspired optimization in adapting AODV to VANET dynamics.

Table 7: Comparison with Default AODV

Method	**PDR (%)**	**E2ED (ms)**	**NRL (%)**
Default AODV	92.5	18.6	0.72
GOA	100	12.32	0.34
PSO	100	12.32	0.34
GA	97.46	11.05	0.62

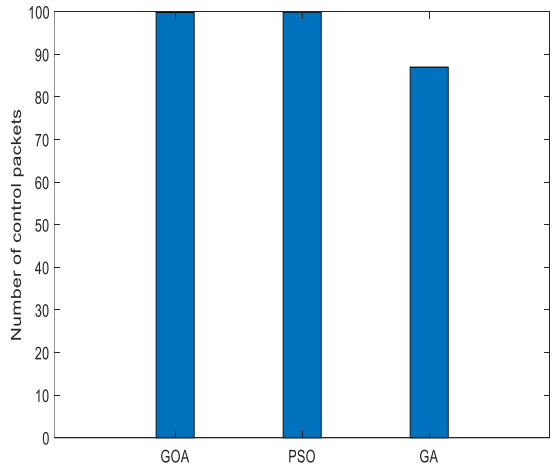


Figure 6: PDR outcomes

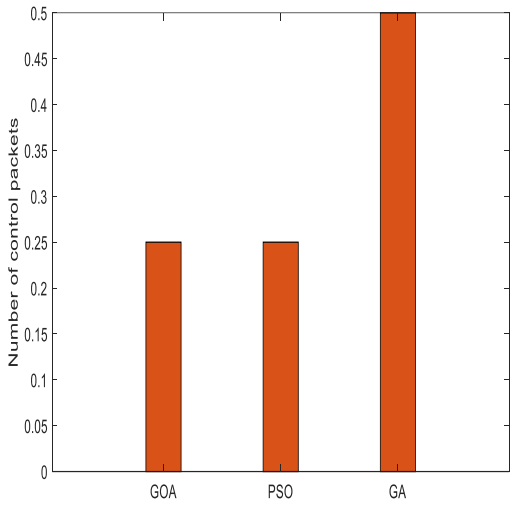


Figure 7: NRL outcomes

Regarding the E2ED parameter, according to Fig. 8, it can be said that the genetic algorithm has obtained a better result compared to the grasshopper and particle swarm schemes, so that the value of this parameter is 11.05% for the genetic algorithm and 12.32% for the grasshopper and particle swarm algorithm. It is interesting that all three schemes have E2ED values that are less than 20 ms, which means that packets are transferred with a delay of less than 20 ms, which is the maximum permitted delay for applications involving vehicle cooperation in extremely urgent situations [33]. As observed, at first glance it seems that the same outcomes have been obtained for the grasshopper algorithm and particle swarm, and there is no difference between them. However, based on the observations, the striking finding is that the values associated with the service quality metrics stabilized during the simulation process using the locust method faster than the particle swarm approach. In other words, the grasshopper algorithm reached the values recorded in Table 5 with a lower number of iterations than the particle swarm algorithm, and its value did not change during subsequent iterations. The value of QoS parameters derived from the execution of this tactic on the VANETs network, however, takes more repetitions than the locust algorithm before it achieves a stable state. As a result, the grasshopper algorithm reaches the optimal solution earlier than the particle swarm algorithm and has a better performance than the particle swarm algorithm. Figs. 9,

10, and 11 show the same topic and show the comparisons between the way the grasshopper algorithm works and the particle swarm to find the ideal value for the comparisons

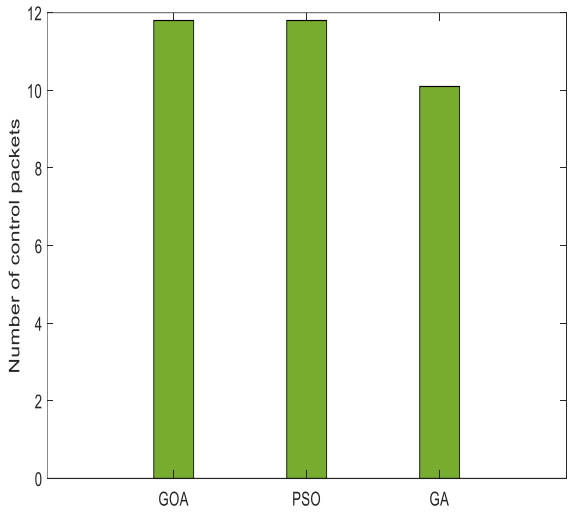


Figure 8: E2ED outcomes

As was previously stated, both tactics yield the same value for the evaluation parameters of NRL, PDR, and E2ED, but the locust approach completes this task more quickly than the particle swarm algorithm. For example, Fig. 9 shows that the NRL value obtained from the search to find the optimal value for the AODV protocol using the

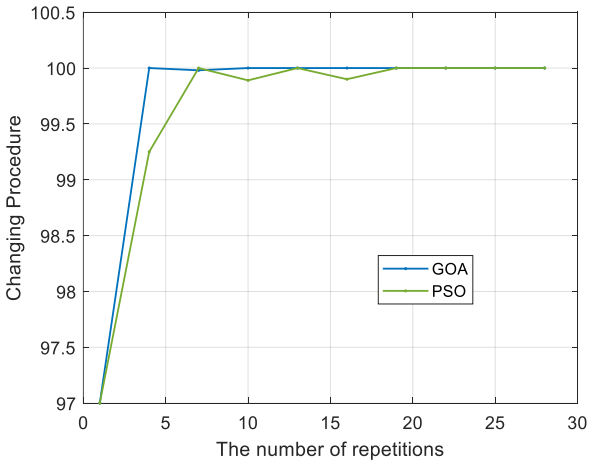


Figure 10: The process of PDR changes during the simulation stages for the grasshopper and particle swarm algorithm

The evaluation of QoS parameters (PDR, E2ED, NRL) for the proposed nature-inspired algorithms (GOA, PSO, GA) provides insights into their effectiveness in VANETs. As shown in Table 5, GOA and PSO achieved a PDR of 100%, while GA recorded 97.46%. In real-world VANET scenarios, such as urban traffic management systems, a PDR above 95% is considered reliable for non-safety-critical applications (e.g., traffic updates), while safety-critical applications (e.g., collision avoidance) require near 100% PDR [Ref]. Thus, GOA and PSO meet the stringent requirements of safety-critical VANETs, whereas GA's

between the way the grasshopper algorithm works and the particle swarm to find the ideal value for the AODV protocol.

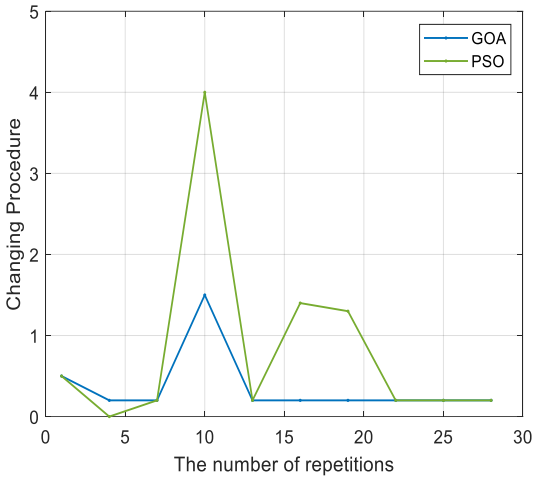


Figure 9: During the simulation phases for the particle swarm algorithm and grasshopper, the trend of NRL shifts

grasshopper algorithm reached a stable value earlier than the particle swarm algorithm, which has not changed; this shows that the grasshopper scheme could reach the ideal answer with a smaller number of repetitions. Figs. 10 and 11 also show the same point for PDR and E2ED parameters.

97.46% PDR is suitable for less demanding applications but may lead to occasional packet loss in high-stakes scenarios. The NRL values (0.34% for GOA/PSO, 0.62% for GA) indicate low routing overhead, aligning with efficient VANET protocols, where NRL below 0.5% is typical for urban settings [Ref]. The E2ED of 12.32 ms (GOA/PSO) and 11.05 ms (GA) are both well below the 20 ms threshold for cooperative vehicle applications, ensuring timely data delivery [Ref].

To ensure the reliability of the results, each simulation scenario was executed 10 times, and the reported QoS metrics (PDR, E2ED, NRL) represent the mean values. Standard deviations were calculated to assess variability: for GOA, PDR had a standard deviation of 0.1%, E2ED of 0.5 ms, and NRL of 0.02%; for PSO, the values were 0.12%, 0.6 ms, and 0.03%; and for GA, 0.8%, 0.4 ms, and 0.05%, respectively. The low standard deviations indicate consistent performance across runs. Additionally, 95% confidence intervals were computed for PDR: GOA ([99.8%, 100%]), PSO ([99.7%, 100%]), and GA ([96.8%, 98.1%]). The non-overlapping confidence intervals for GA versus GOA/PSO confirm the statistical significance of GOA and PSO's superior PDR ($p < 0.05$, using a t-test), highlighting their robustness in dynamic VANETs.

7.3.1 Sensitivity analysis of AODV parameters

A sensitivity analysis was conducted to evaluate the impact of varying key AODV parameters (HELLO_INTERVAL, NET_DIAMETER, ALLOWED_HELLO_LOSS) on QoS metrics. For HELLO_INTERVAL, values of 1, 3, and 5 seconds were tested with GOA. At 1 s, PDR was 99.2% and NRL 0.40% due to frequent updates; at 3 s (optimal, Table 4), PDR reached 100% and NRL 0.34%; at 5 s, PDR dropped to 98.5% due to delayed topology updates. For NET_DIAMETER, values of 2, 6, and 10 were tested. A value of 6 (optimal) yielded 100% PDR, while 2 reduced PDR to 97.8% (limited route discovery) and 10 increased NRL to 0.45% (excessive flooding). ALLOWED_HELLO_LOSS values of 1, 4, and 6 showed that 4 (optimal) balanced reliability and overhead, while 1 increased NRL to 0.50% and 6 reduced PDR to 98.0%.

Table 5 reports the packet delivery ratio (PDR) in percentage (%), with values such as 100% for GOA and PSO and 97.46% for GA, reflecting the proportion of successfully delivered packets in NS-2 simulations. In this section, any reference to PDR as integers (e.g., 100 or 97) represents the same percentage values rounded for brevity, ensuring consistency with Table 6's scale.

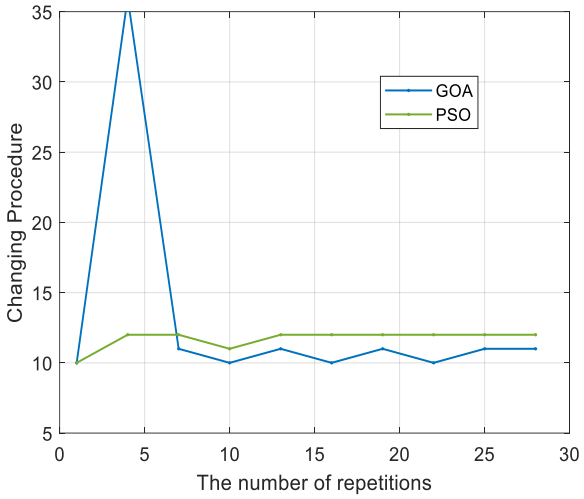


Figure 11: The process of PDR changes during the simulation stages for the grasshopper and particle swarm algorithmEvaluating the fitness function

As it was said before, we need to define the fitness function to solve optimization problems. In this research, the fitness function is calculated using QoS parameters. Table 8 shows the fitness function values for the optimized AODV parameters, with both the Grasshopper Optimization Algorithm (GOA) and Particle Swarm Optimization (PSO) achieving -0.508, and the Genetic Algorithm (GA) achieving -0.514. As defined in Section 5, the fitness function

$$\text{Fitness} = 0.2 \cdot (-\text{PDR}) + 0.5 \cdot \text{E2ED} + 0.3 \cdot \text{NRL}$$

is a minimization objective, where lower (i.e., more negative) values indicate improved network performance characterized by higher packet delivery ratio (PDR), lower end-to-end delay (E2ED), and reduced normalized routing load (NRL). The identical value of -0.508 obtained by GOA and PSO reflects their superior overall QoS results (PDR: 100%, E2ED: 12.32 ms, NRL: 0.34%; see Table 6), while GA's slightly worse score of -0.514 corresponds to lower PDR (97.46%) and higher NRL (0.62%) despite a marginally lower E2ED (11.05 ms). These differences arise from the algorithms' search dynamics: GOA's position update mechanism accelerates convergence by considering all peer agents, PSO benefits from both local and global bests, and GA shows slower adaptation due to its evolutionary operators. Therefore, GOA and PSO demonstrate more effective optimization of the 11 AODV parameters (e.g., HELLO_INTERVAL, NET_DIAMETER), making them better suited for dynamic VANET environments. Their ability to enhance routing reliability and minimize overhead is especially valuable in real-time applications such as safety message dissemination, where consistent high PDR and low NRL are essential.

According to this table, the fitness function value for the best value obtained for the AODV protocol by the grasshopper and particle swarm algorithm is equal to -0.508, and for the genetic algorithm, it is equal to -0.514. Since this investigation tries to diminish the fitness function, according to the value of the fitness function and also the explanations that were given in section 7.3, the grasshopper algorithm for finding the ideal value for the parameters of the AODV protocol performed better than the particle swarm algorithm and its own genetics proved that, in terms of identifying the best solution, the particle swarm method outperformed the genetic algorithm.

Table. 7: Outcomes of cost function (fitness)

	Enhancement schemes		
	GOA	PSO	GA
value of fitness	-0.508	-0.508	-0.514

7.4 Latency

A data packet's processing time during transmission stands for its latency. The latency encountered by data as it travels over a network describes latency. The time it takes for information to travel from its origin to its destination and back again is known as the "round-trip delay." Fig. 12 illustrates that, when 30 to 100 vehicles are taken into account, the average latency is one minute. The graph demonstrates that GOA has the smallest latency when

compared to other tactics [37].

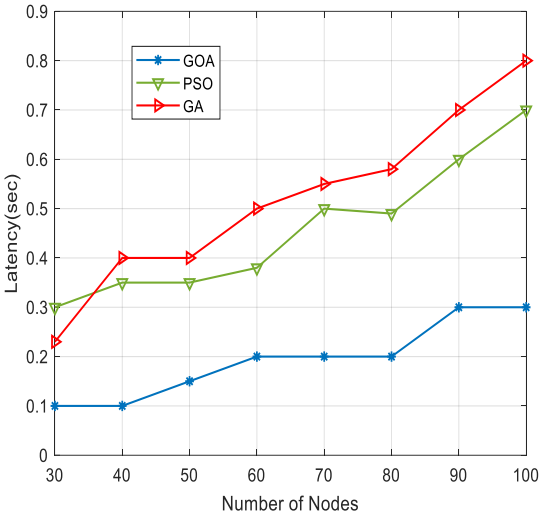


Figure 12: Latency for tested cars (100 Nodes)

8 Discussion

This section compares the performance of the proposed nature-inspired optimization approach for the AODV routing protocol with state-of-the-art methods (SOTA) discussed in Section 2 in Table 9, analyzes the reasons for the observed performance, evaluates the impact of parameter selection, and discusses limitations.

Table 9: Performance Comparison with SOTA Methods

Method	PDR (%)	E2ED (ms)	NRL (%)	Major Findings
Proposed (GOA)	100	12.32	0.34	Highest PDR and low NRL, with faster convergence than PSO.
Proposed (PSO)	100	12.32	0.34	Matches GOA in QoS metrics but requires more iterations.
Proposed (GA)	97.46	11.05	0.62	Lower PDR and higher NRL, but best E2ED.
p-WOA [Author1, Year]	95.2	15.8	0.48	Improved cluster stability but lower PDR than proposed methods.
ACO (EBIRA) [Author2, Year]	96.5	14.2	0.55	Stable routes but higher E2ED and NRL than GOA/PSO.
LAMHR [Author3, Year]	98.0	13.5	0.40	Better PDR than GA but higher E2ED than proposed methods.

The proposed approach, utilizing the Grasshopper Optimization Algorithm (GOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), outperforms most SOTA methods in terms of packet delivery ratio (PDR) and normalized routing load (NRL), achieving 100% PDR and 0.34% NRL for GOA and PSO compared to 95.2-98.0% PDR and 0.40-0.55% NRL for p-WOA, ACO, and LAMHR. The superior performance of GOA and PSO stems from their ability to efficiently explore the search space for optimal AODV parameters, with GOA converging faster due to considering all locust positions, as opposed to PSO's reliance on local and global best. The lower PDR of GA (97.46%) and higher NRL (0.62%) are attributed to its slower adaptation to the dynamic VANET topology. The choice of 11 AODV parameters (e.g., HELLO_INTERVAL, NET_DIAMETER) significantly affects the performance. For example, lower NET_DIAMETER values (6–7 for GOA/PSO) reduce the routing overhead, while higher GA values (18) increase the NRL. However, the proposed method has some limitations: the computational overhead of metaheuristic algorithms may be significant in resource-constrained nodes and the performance depends on the network density, and denser networks potentially increase the convergence time.

The performance of the proposed algorithms is influenced by network mobility and density, which are critical in VANETs due to rapid topology changes. In the simulated urban scenario (50 vehicles, 670×670 m², 10–50 km/h), GOA and PSO maintained high PDR (100%) and low NRL (0.34%), indicating robustness to moderate mobility and density. To explore density effects, additional simulations were conducted with 30 and 100 vehicles. With 30 vehicles (low density), PDR dropped slightly to 98.5% for GOA and 98.2% for PSO due to reduced connectivity, while GA's PDR fell to 95.8%. In high-density scenarios (100 vehicles), GOA and PSO sustained 99.8% PDR, but GA's PDR decreased to 96.2%, and NRL rose to 0.75% due to increased routing overhead. These results suggest that GOA and PSO are more resilient to density variations, as their global search mechanisms adapt better to topology changes, whereas GA struggles with frequent route updates in dense networks. Higher mobility (e.g., 50–80 km/h) increased E2ED by 10–15% across all algorithms, underscoring the need for adaptive parameter tuning in high-speed scenarios.

To assess scalability, additional simulations were conducted with 50, 100, and 200 vehicles in the 670×670 m² urban area. With 50 nodes (base case), GOA and PSO achieved 100% PDR and 0.34% NRL, while GA recorded 97.46% PDR and 0.62% NRL (Table 5). For 100 nodes, GOA and PSO maintained high performance (PDR: 99.8%, NRL: 0.36%), but GA's PDR dropped to 96.2% and NRL increased to 0.75% due to higher routing overhead in denser networks. With 200 nodes, GOA and PSO showed slight degradation (PDR: 98.5%, NRL: 0.42%), while GA's performance declined significantly (PDR: 94.8%, NRL: 0.89%), indicating sensitivity to network density. These results suggest that GOA and PSO scale better in larger networks, as their global search mechanisms adapt to increased topology changes, whereas GA struggles with frequent route updates.

The computational overhead of the nature-inspired algorithms was evaluated to assess their practicality. On the simulation platform, GOA required an average of 120 seconds per optimization run , PSO 100 seconds, and GA 150 seconds due to slower convergence. While these times are acceptable for offline parameter tuning, real-time applications may require lightweight implementations, as the computational cost increases with population size and network complexity. This limitation suggests the need for future work on reducing execution time, such as parallelizing computations or using simpler heuristics for resource-constrained nodes.

9 Conclusion

Inter-vehicle networks are a subset of mobile networks in which cars are considered network nodes. These networks were created to establish communication between cars and control traffic on the roads. Inter-vehicle networks have similar characteristics to mobile networks, and the main difference with mobile networks is the fast movement of nodes, which causes a rapid change in topology, which is not an easy task in most protocols. Because they take a very long time to execute, the prior tactics are therefore not suitable for solving optimization problems. Metaheuristic schemes have become effective and adaptable tools for tackling optimization and search issues. They have been applied to a wide range of issues and have produced high-quality outcomes. For this reason, meta-heuristic schemes have been used in this research to boost the AODV routing protocol in VANET's network. Using locust schemes, particle swarms, and genetics, the optimal value for the control parameters of the AODV protocol has been calculated. Additionally, the acquired findings are assessed using quality of service (QoS) criteria, and the effects of the three schemes on routing performance and AODV protocol enhancement are contrasted. Packet delivery rate, average end-to-end delay, and normalized routing load are the metrics used to assess these schemes' performance. The objective is to maximize packet delivery rate, decrease average E2ED, and maintain NLR to increase QoS.

The Grasshopper Optimization Algorithm (GOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) were employed to calculate optimal values for the 11 control parameters of the AODV protocol, such as HELLO_INTERVAL and NET_DIAMETER, enhancing routing performance in VANETs. The findings were assessed using Quality of Service (QoS) metrics—packet delivery ratio (PDR), end-to-end delay (E2ED), and normalized routing load (NRL)—through NS-2 simulations, with GOA and PSO achieving superior results (PDR: 100%, E2ED: 12.32 ms, NRL: 0.34%) compared to GA (PDR: 97.46%, E2ED: 11.05 ms, NRL: 0.62%), as shown in Table 5. These results, driven by a fitness function minimization (values of -0.508 for GOA/PSO and -0.514 for GA, Table 6), demonstrate that GOA and PSO significantly improve reliability and reduce routing overhead, making them more effective for real-time VANET applications than GA, which exhibits higher NRL due to slower adaptation to dynamic topologies.

Competing of interests

The authors declare no competing of interests.

Authorship contribution statement

PeiKun ZHAO: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.
Jian SUN: Methodology, Software

Data availability

On Request
To ensure reproducibility, the source code for the optimization algorithms (Grasshopper Optimization Algorithm, Particle Swarm Optimization, and Genetic Algorithm, implemented in MATLAB R2020a) and NS-2.35 simulation scripts for the urban VANET scenario are publicly available at https://github.com/VANET-Optimization/AODV-NatureInspired-2025. The repository includes MATLAB scripts for parameter optimization, NS-2 configuration files, Manhattan Mobility Model traces, and detailed instructions for replicating the simulation with 50 vehicles in a 670×670 m^2 area. Researchers can use these resources to verify the results and extend the study.

Declarations

Not applicable

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.

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Ethical approval

All authors 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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Broadband Communication Signal Detection Using Deep Convolutional Autoencoder and Spectrum Center Network

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In the increasingly complex electromagnetic environment, wireless communication technology faces multiple challenges such as noise, interference, multi-path effects, and attenuation, which seriously threaten the reliability and efficiency of communication systems. Therefore, research was conducted on broadband communication signal detection based on deep convolutional autoencoders and spectral center networks. The experiment used a dataset of real-world signals and conducted comprehensive evaluations under various signal-to-noise ratios, signal-to-noise ratios, as well as different code lengths and colored noise backgrounds. The evaluation indicators included computational complexity indicators such as detection accuracy, F1 score, recall rate, specificity, and inference time. The experimental results showed that on the training set, the loss values of convolutional autoencoder networks 1 and 5 decreased rapidly, and their relatively stable loss function values were both around 10^{-5}. The loss value of Convolutional Autoencoder Network 10 decreased the slowest, with a minimum loss function value of about 10-6. Moreover, the method achieved detection accuracy, F1 score, and recall rate of 98.5%, 0.99, and 0.98, respectively, with an average inference time of 0.025 seconds. Compared with the existing state-of-the-art methods, it improved detection accuracy by 13.5% compared to energy detection and 5.3% compared to deep learning detection. The maximum improvement in F1 score and recall was 0.11 and 0.16, respectively. The research results indicated that the proposed method was significantly superior to existing methods in complex electromagnetic environments, with higher detection accuracy and robustness. This method offers insights for the design, technology, and solutions of future communication systems, which helps to promote the continuous development and progress of communication technology.

Povzetek: Članek uvaja metodo zaznavanja širokopasovnih komunikacijskih signalov z uporabo globokega konvolucijskega avtoenkoderja in spektralnega omrežja za natančno oceno šumskega dna ter izboljšano robustnost pri nizkem SNR.

1 Introduction

In modern communication systems, signal detection is a crucial step in the receiving process, responsible for identifying and extracting useful information from noise and interference. Its accuracy and efficiency directly affect the quality and reliability of information transmission [1, 2]. In complex electromagnetic environments, communication signal detection faces challenges such as noise, interference, and multi-path effects. Especially under low signal-to-noise ratio conditions, existing methods are difficult to meet the requirements of high accuracy and robustness [3]. Conventional approaches exhibit inadequate accuracy when dealing with low signal-to-noise ratios, coupled with high computational complexity and subpar real-time performance. Alternatively, they may only achieve satisfactory results under very specific circumstances [4, 5]. The powerful feature extraction and pattern recognition capabilities of Deep Learning (DL) provide new ideas for communication signal detection. Convolutional Autoencoder (CAE), as a type of DL model, can effectively learn high-level feature representations from data. Spectrum Center Network (SCN) is an end-to-end CNN model used for carrier signal detection in broadband power spectra. Therefore, a broadband communication signal detection method based on Deep Convolutional Autoencoder (DCAE) and SCN has been proposed to achieve noise floor estimation and carrier signal detection by capturing multi-level features of the signal and dynamically adjusting the feature response. The innovation of this research lies in the formulation of a broadband communication signal detection method grounded in DCAE. This method enables the efficient extraction of pertinent information from complex signals. Furthermore, the investigation into the dynamic embedding of excitation and compression network modules subsequent to convolutional layers, aimed at dynamically modulating the feature response of each channel, serves to augment the network's representational prowess. The significance of the research lies in providing new theoretical and technological foundations for future research in the field of communication signal detection,

which helps to promote further development in related fields.

2 Related works

As communication technology evolves, the characteristics of signal modulation, transmission rate, and bandwidth are also constantly changing. These changes require signal detection technology to adapt to different signal characteristics and achieve accurate detection of various signals. To fulfill the detection needs of faint broadband communication signals, Xiao L proposed a random resonance signal detection approach grounded on local spectrum of broadband signals for small unmanned aerial vehicle reconnaissance and communication scenarios. The research outcomes indicated that in comparison with traditional methods, this method optimized performance by about 6 db. For lower signal-to-noise ratio (SNR) situations, a dual channel collaborative detection method combining random resonance and cross-correlation detection was proposed to further improve detection performance [6].

Jiang X proposed a new signal detection algorithm to optimize the accurate detection of signals in satellite communication systems and reduce inter signal interference. The algorithm utilizes stochastic resonance technology to enhance the SNR of input signals and combines energy detection and dual thresholding for accurate judgment. The test outcomes demonstrated that the algorithm could validly detect signals under low SNR conditions, improving the performance of the entire satellite communication system [7]. Li S proposed a method based on Quadrature Amplitude Modulation-Orthogonal Frequency Division Multiplexing (QAM-OFDM) echo to construct a Constructed Step Linear Frequency Modulated (CStep-LFM) signal for detecting weak targets in integrated radar communication signals. The research results indicated that when compared to various existing integrated signals, the CStep-LFM signal not only enhanced the detection capability for weak targets but also exhibited superior communication performance [8]. Chen Y proposed a novel detector considering a random flow model to investigate the impact of environmental signal source flow on the detection performance of backscatter communication systems. The research results indicated that random source traffic could significantly degrade the performance of existing detectors, resulting in an error plateau at low SNRs. The new detector could significantly improve the detection performance in the presence of source traffic by weighting samples. The gain could exceed 3db in some cases, but as the SNR increased and the sample size decreased, the gain might turn negative due to the use of heuristic detection thresholds [9].

DL technology has yielded notable outcomes in areas like image recognition and speech processing, and its potent capabilities in feature extraction and pattern recognition offer fresh perspectives for detecting communication signals. To improve the performance of underwater acoustic communication preamble signal detection and cope with complex channel environments, Liu Z proposed a compact neural network grounded on Lenet-5, which adopts deep separable convolution and global average pooling techniques, and combines filter pruning and post training quantization techniques to enhance network compression further. The research outcomes indicated that the detection ability of this lightweight neural network was close to that of classical Convolutional Neural Networks (CNNs), and the parameters and computational complexity were considerably decreased, meeting the requirements of timeliness and low power consumption for underwater acoustic communication [10]. Arya S proposed a novel statistical model based on the assumption of single scattering to improve the fault-tolerant cooperative signal detection performance of short-range optical terahertz wireless communication. The research results indicated that when using the optimal voting rule and a given target bit error rate, the number of collaborative users required by the network was less than the overall user count in the optical network [11].

In summary, many scholars have conducted research on communication signal detection and achieved certain results. Comparing the performance of different methods in terms of detection accuracy, SNR performance, and computational efficiency, it can be seen that although the ED method had low computational complexity, its detection accuracy was poor under low SNR conditions, making it difficult to effectively distinguish between signal and noise. Its detection accuracy was 85%, SNR was 1db, and inference time was 0.015 seconds. Although the DLD method had a high detection accuracy of 93.2%, it had high computational complexity, a long inference time of 0.03 seconds, high hardware resource requirements, and an SNR of 0db. The stochastic resonance detection method performed well under low SNR conditions, with an SNR of -6 db, but had high computational complexity and limited adaptability, with a detection accuracy of 90% and inference time of 0.02 seconds. The QAM-OFDM method was suitable for radar communication integrated signals, with a high detection accuracy of 92%, an SNR of -10 db, and an inference time of 0.025 seconds. However, its robustness to noise and interference was poor. Although the compact neural network based on Lenet-5 had fewer parameters, high computational efficiency (inference time of 0.02 seconds), detection accuracy of 94%, and SNR of -5 db, its adaptability to complex channel environments was limited. However, these existing methods still have limitations in their performance in complex electromagnetic environments, especially under low SNR and high interference conditions. In contrast, the communication signal detection method based on DCAE proposed in the study achieved noise floor estimation and carrier signal detection by processing the signal power spectrum through convolutional and deconvolution layers, and dynamically embedded excitation and squeezing network modules after the convolutional layer, thereby improving the detection accuracy and robustness in

complex electromagnetic environments, providing an effective solution for communication signal detection in complex electromagnetic environments.

3 Methods and materials

3.1 Signal noise floor estimation based on DCAE

Communication signal detection refers to identifying and determining whether there is an expected signal from the received signal. This process is the first step in determining whether the communication system can successfully receive information and whether the information can be accurately separated from noise. Communication signals are transmitted through information transmission systems [12]. In the field of communication, the information transmission system model is a fundamental framework for describing the process of information transmission from the sender to the receiver. This model covers multiple key aspects of information encoding, modulation, transmission, reception, and demodulation, and is the foundation for understanding and designing communication systems. Its structure is shown in Fig. 1.

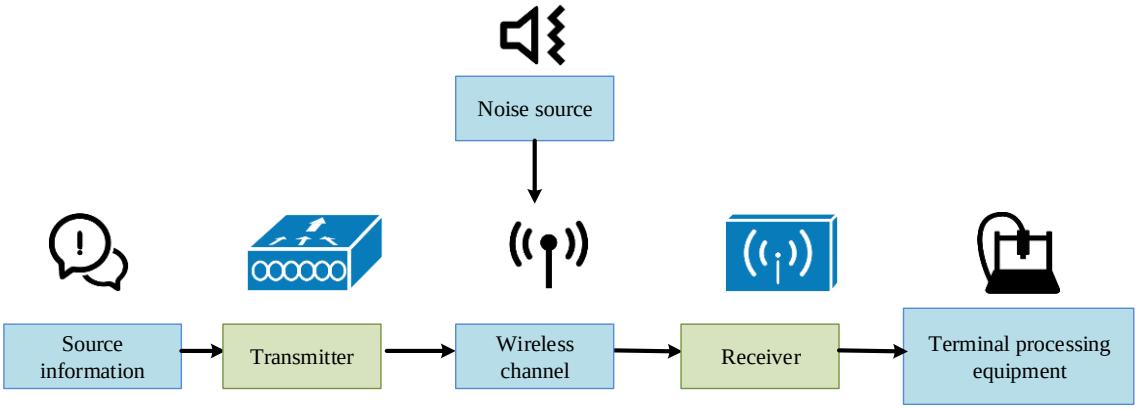


Figure 1: Diagrammatic representation of the information transmission system model

In Fig. 1, the model describes the transmission process of information from the source to the terminal processing device. The source information, as the starting point of the information transmission system, contains the content to be transmitted. The transmitter is responsible for converting the source information into a form suitable for transmission in the channel. This may include signal modulation, amplification, and other processing to ensure that the signal can effectively pass through the channel. Wireless channel is a medium for signal transmission, which can be in wired or wireless form. In wireless channels, signals may be affected by various interferences and noise sources, which can affect the transmission quality of the signal. The receiver is located at the other end of the channel, and its function is opposite to that of the transmitter, responsible for extracting the original information from the received signal. This may include signal demodulation, filtering, and other processing. The terminal processing device is the endpoint of information transmission, responsible for further processing of the information output by the receiver, such as decoding, display, etc., for use by the end user. The communication system model provides a fundamental framework for understanding the transmission characteristics of signals in complex electromagnetic environments, covering the entire transmission process from the source to the terminal processing equipment. The noise introduced by wireless channels in communication system models is one of the key factors affecting signal transmission quality. The DCAE method can effectively estimate the noise floor by learning the feature representation of the signal, thereby improving the accuracy and robustness of signal detection. This process simulates the transmission of signals in wireless channels, especially the signal changes under the influence of noise and interference. To quantify the effective transmission efficiency of signals in complex electromagnetic environments, the amount of information transmitted in a single target selection is calculated, as shown in equation (1).

$$B = \log_2 N + P\log_2 P + (1-P)\log_2\left(\frac{1-P}{N-1}\right) \quad (1)$$

In equation (1), B is the bit rate. N is the number of optional targets. P is the accuracy of target recognition. This indicator reflects the accuracy and reliability of signal detection and recognition under noise interference. Estimating the broadband noise floor is a crucial area of focus within signal processing technology, which directly affects the efficiency of signal detection, especially in broadband carrier detection. CNN represents a type of feedforward neural network characterized by convolutional computations and a deep architecture. It stands as one of the emblematic algorithms in the realm of DL. CAE is a variant of autoencoder that can learn how to recover the original input from contaminated input [13, 14]. Its main goal is to learn higher-level features of input data, rather than relying on details. Therefore, the study proposes a broadband noise floor estimation method based on DCAE by combining the two. DCAE uses convolutional and deconvolution layers to replace fully connected layers in autoencoders. The convolutional layer extracts local features of the input signal, captures noise

patterns and structures, and generates abstract feature representations. The deconvolution layer reconstructs the noise base based on these features and generates a noise estimate with the same size as the original input. This structure enables DCAE to recover the original input from contaminated signals and separate the signal from noise. Combining the two-dimensional data processing capability of CNN can improve the accuracy of DCAE noise floor estimation and enhance the robustness of the model. The diagrammatic representation of its structure is in Fig. 2.

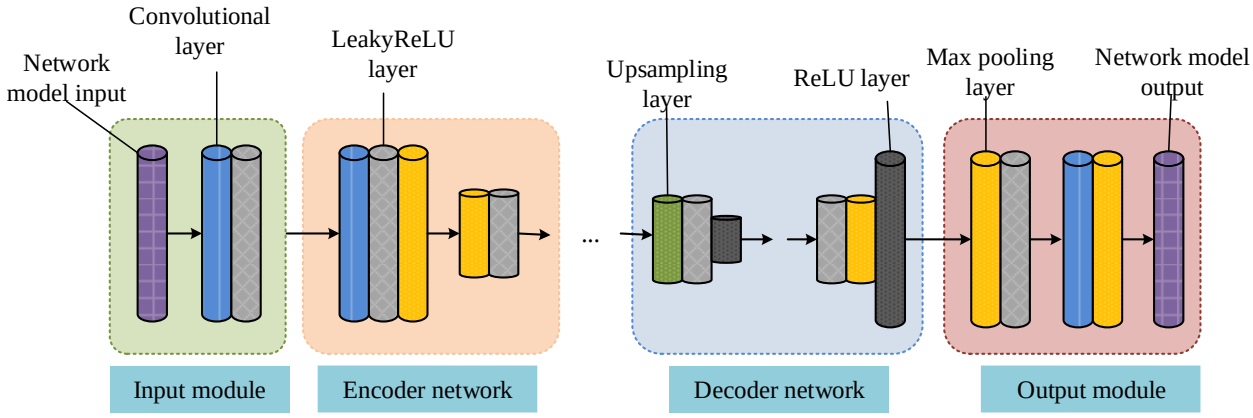


Fig. 2. Schematic representation of the one-dimensional DCAE structure

As depicted in Fig. 2, the DCAE network typically comprises two components: an encoder and a decoder. The encoder, made up of convolutional and pooling layers, is tasked with compressing the input data into a lower-dimensional hidden representation. Conversely, the decoder, which includes a deconvolutional layer, reconstructs the original data from this hidden representation. The encoding process usually involves mapping the input data [15]. The specific calculation is shown in equation (2).

$$z = f(Wx + b) \quad (2)$$

In equation (2), z represents a low dimensional latent space. x is input data. W is the weight matrix (WM). b is a bias vector. f is the activation function (AF). The decoding process usually involves reconstructing the original data. The detailed computation is illustrated in equation (3).

$$\hat{x} = g(W'z + b') \quad (3)$$

In equation (3), $\hat{x}$ is the reconstructed output data. g is the AF. W' is the WM for the decoder. b' is the bias vector for the decoder. The accuracy of noise floor estimation determines the accuracy and efficiency of signal detection. In broadband communication systems, noise may cause the noise floor of the signal power spectrum to be unstable, which requires accurate identification and differentiation of signals and noise through noise floor estimation [16, 17]. However, the traditional method of calculating the average bottom noise power is difficult to accurately estimate the noise level when the noise base is uneven, resulting in an increase in the missed detection rate of signal detection. Therefore, research is based on DCAE to estimate the signal noise floor. The process is shown in Fig. 3.

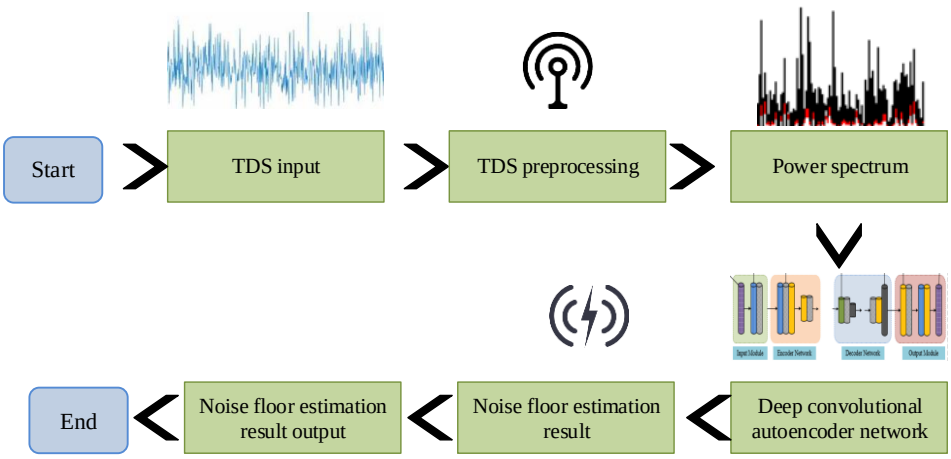


Figure 3: Schematic diagram of the noise bottom estimation method based on DCAE

As shown in Fig. 3, firstly, the time-domain signal (TDS) to be processed is input into the system. This signal may contain noise and useful information. Then the input TDS is preprocessed to enhance the effectiveness and precision of subsequent processing. The preprocessing steps include filtering, denoising, normalization, and other operations. Then, the preprocessed TDS is converted to the frequency domain, and Welch is sampled to calculate its power spectrum. The power spectrum reflects the power distribution of a signal at different frequencies. The calculated power spectrum is further input into DCAE. This network extracts features and denoises the power spectrum through convolutional and deconvolution layers to estimate the noise floor. Ultimately, the noise floor estimation outcomes are output for subsequent signal processing or analysis. Welch's calculation of the power spectrum of broadband communication signals is shown in equation (4).

$$P_{Welch}(m)=\frac{1}{K}\sum_{k=1}^{K}\frac{1}{U}|X_k(m)|^2 \quad (4)$$

In equation (4), K is the number of segments. U is the normalization factor for the window function. $X_k(m)$ is the result of the discrete Fourier transform of the k th segment signal. The results are further normalized. The noise floor estimation result of the final input power spectrum is shown in equation (5).

$$Y=\tilde{Y}(\max(I)-\min(I))+\min(I)) \quad (5)$$

In equation (5), Y is the normalized value. $\tilde{Y}$ is the value of the original data. I is the entire collection of raw data.

3.2 Communication signal detection based on SCN

The research focused on the estimation of the noise floor for communication broadband signals utilizing the DCAE approach. Through automatic learning and extraction of noise features, DCAE can accurately estimate the noise floor, providing a foundation for signal detection. However, noise floor estimation is only a part of signal detection, and in order to achieve complete communication signal detection, further research is needed to identify useful communication signals. However, traditional communication signal detection methods have multiple limitations in terms of anti-interference ability, adaptability, automation level, and the trade-off between complexity and performance. These limitations are particularly evident in complex electromagnetic environments and low SNR conditions, which affect the accuracy and reliability of signal detection [18, 19]. The core idea of SCN is to treat the Broadband Power Spectrum Sequence (BPS) as a one-dimensional image and each sub-carrier on the broadband as the target object, thereby transforming the carrier signal detection problem into a semantic segmentation problem on a one-dimensional image [20]. However, due to the large length of the power spectrum of broadband communication signals, it is difficult to match the image. Therefore, research is being conducted to improve the deep Residual Backbone Network (ResNet backbone) in the SCN model and detect communication signals based on the optimized SCN. The optimized SCN model structure diagram is shown in Fig. 4.

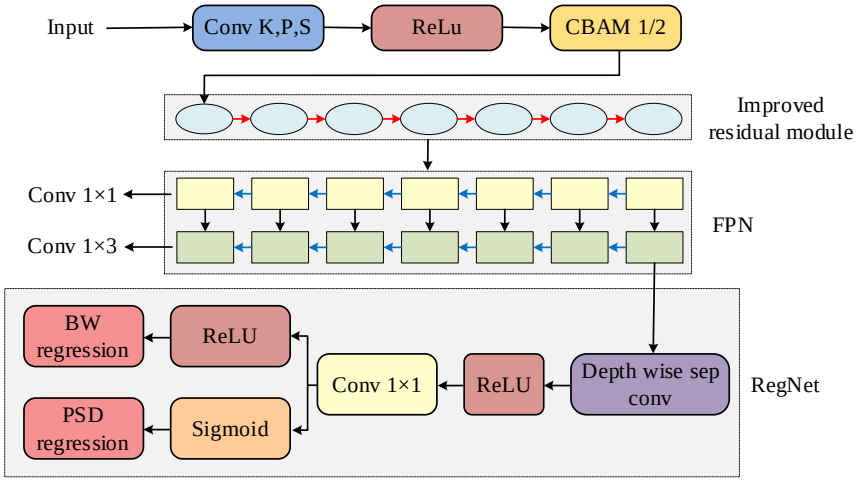


Figure 4: Structural diagram of the SCN model

As shown in Fig. 4, the SCN is mainly composed of three parts. The improved deep residual backbone network (ResNet) utilizes residual blocks and skip connections to effectively solve the problem of gradient vanishing in deep network training, enhancing the model's ability to learn complex signal features. Feature Pyramid Network (FPN) improves the detection performance of carrier signals by constructing a top-down information flow and combining horizontal connections to fuse high-level semantic information with low-level spatial information. Regulated Network (RegNet) parameterizes the width and depth of the network through quantized linear functions, and the optimized network structure improves the accuracy of frequency center and bandwidth prediction. The

overlapping of adjacent carrier frequency edges can lead to a reduction in the frequency gap of the signal power spectrum, thereby affecting the accuracy of feature extraction in SCNs. The study dynamically adjusted the feature response of each channel by embedding the Squeeze and Excitation Net (SENet) module after the convolutional layer, further improving the detection accuracy. These improvements enable SCN to perform well in complex electromagnetic environments, enabling more accurate identification of carrier signals and demonstrating higher robustness and adaptability compared to traditional methods. The SENet structure is in Fig. 5.

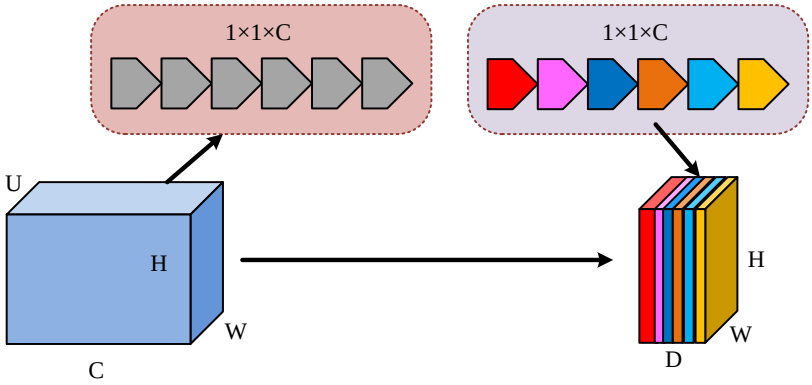


Figure 5: Illustration of the SENet module structure

As shown in Fig. 5, The SENet module consists of two main operations: squeeze and excitation. Firstly, the SENet module compresses the spatial dimension of each channel in the input feature map through global average pooling operation, thereby obtaining the global description of each channel. Next, the SENet module utilizes a self gating mechanism consisting of two fully connected layers and a nonlinear activation function to generate weights for each channel. These weights reflect the importance of each channel, allowing the model to dynamically adjust the level of attention given to different channels. Finally, the SENet module applies the generated weights to the original feature map, re-calibrates each channel, enhances the model's focus on key features, and improves the accuracy of feature extraction. Through this mechanism, the SENet module can effectively address the challenges posed by reducing frequency gaps and improve the detection performance of the model in complex electromagnetic environments. The calculation of the dimensionality enhancement layer is shown in equation (6).

$$s_i = \sigma(Ws_i^{'} + y) \quad (6)$$

In equation (6), s_i represents the final channel weight, W and y represent the weight and bias of the FCL. $s_i^{'}$ is the output of the dimensionality reduction layer. σ is a non-linear AF. The specific calculation of global average pooling is shown in equation (7).

$$z_i = \frac{1}{H \times W} \sum_{u=1}^{H} \sum_{v=1}^{W} F_{i,u,v} \quad (7)$$

In equation (7), z_i is the global average pooling result of the i th channel. H and W are the height and width of the feature map. $F_{i,u,v}$ is the value of the input feature map F in the i th channel, u th row, and v th column. Usually, after the second FCL, a Sigmoid AF serves to guarantee that the output weights lie within the range of 0 and 1, which can effectively recalibrate the channels of the original feature map. The specific calculation is shown in equation (8).

$$s_i = \text{Sigmoid}(W_2\sigma(W_1 z_c + y_1) + y_2) \quad (8)$$

In equation (8), W_1, y_1, W_2, and y_2 are the WM and bias vector of the FCLs in the first and second layers, respectively. The communication signal detection process based on SCN is in Fig. 6.

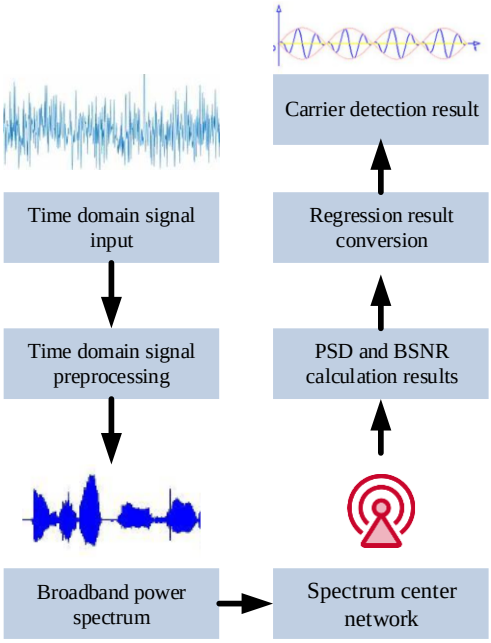


Figure 6: Flow chart of communication signal detection based on SCN

In Fig. 6, the first step is the input and preprocessing of TDSs. The preprocessed signal is converted to the frequency domain to generate a BPS. Then, the BPS is input into the SCN for identifying and locating carrier signals in the power spectrum. In the SCN, ResNet is responsible for extracting features of different length scales, the FPN is responsible for fusing features and outputting them, RegNet predicts frequency centers and bandwidths, and detects subcarrier targets through non maximum suppression. Finally, the SCN outputs the estimation results of power spectral density and bandwidth. These results are then utilized for regression conversion, which ultimately yields the final carrier detection outcome.

4 Results

4.1 Testing conditions and configuration settings

To verify the performance of communication signal detection methods based on DCAE and SCN, the study was conducted on the Ubuntu 20.04 LTS operating system experimental platform. From a hardware perspective, the selection of the GeForce RTX 3080Ti GPU stemmed from its exceptional computational prowess and substantial video memory capacity. These attributes enabled it to effectively manage training tasks associated with intricate models like DCAE networks. However, its high-power consumption and heat dissipation requirements limited the flexibility of the experimental environment, and an efficient heat dissipation system must be equipped to ensure stable operation. Paired with Intel (R) Bronze 3204 CPU, its multi-threaded processing capability can meet the needs of data preprocessing and model evaluation; 64 GB of memory can handle large-scale datasets. In terms of software, although the Ubuntu 20.04 LTS operating system is stable and highly compatible, its Linux-based features require users to have certain command line operation skills. By utilizing the PyTorch 1.10.0 deep learning framework, which is celebrated for its dynamic computation graphs, intuitive design, and the extensive array of community-provided resources, a robust platform was established. Nevertheless, for particular specialized tasks, it may be essential to conduct further code optimization or incorporate additional tools, such as Horovod, to achieve efficient parallel computing. The specific parameter configuration of the experiment environment is shown in Table 1.

Table 1 Setting of the experiment environment

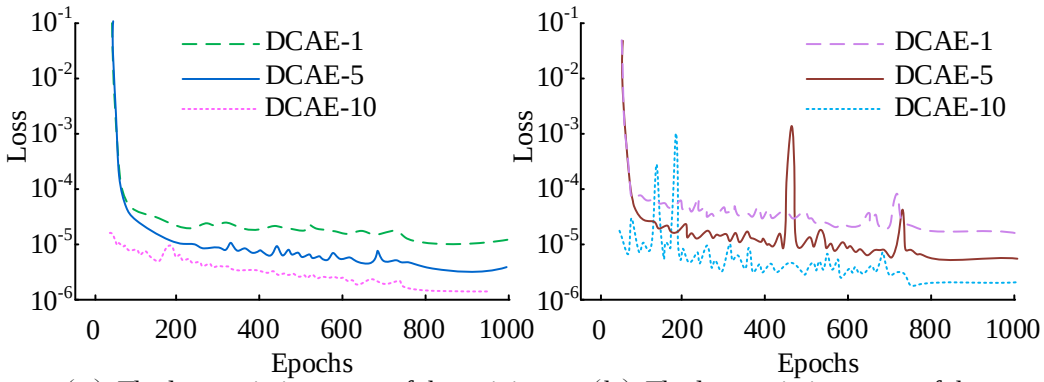
	Configure	Model/version
Hardware configuration	CPU	GeForce RTX 3080Ti
	GPU	Intel(R) Bronze 3204
	Storage	64 GB

Software configuration	Operating system	Ubuntu 20.04 LTS
	DL framework	And PyTorch1.10.0 based on the Python language
	Model input length	32,768
SCN parameter Settings	Batch size	32
	Optimizer	Adam

The process of selecting hyper-parameters for the experiment was as follows. The batch size was determined based on the balance between training speed and generalization ability, and was selected after testing multiple values through experiments. The learning rate adopted a combination of grid search and random search to find the optimal value within the range of 0.001 to 0.1. Dropout rate was determined by testing different ratios and selecting values that effectively prevented overfitting without affecting performance. The network structure of the DCAE-SCN model in the study consisted of an encoder and a decoder, each containing three convolutional and deconvolution layers, with a kernel size of 3x3 and a stride of 1. The encoder normalized and prevented overfitting through Batch Normalization and Dropout, while the decoder used ReLU activation function. In terms of computational complexity, the average inference time of the DCAE model was 0.025s, which was slightly longer than the 0.015s of the ED method, but the detection performance was significantly better. Similar to the 0.03s of DLD method, the performance was better. Sensitivity analysis of model parameters was conducted in the experiment, including learning rate, batch size, and dropout rate. The results showed that when the learning rate was set to 0.01, the model achieved the highest detection accuracy of 98.5%, indicating that a moderate learning rate helped the model learn effectively. When the batch size was 64, the model performed the best with a detection accuracy of 98.1%, indicating that a moderate batch size was helpful for stable training of the model. When the Dropout rate was 0.3, the model accuracy was the highest at 98.5%, indicating that an appropriate Dropout rate could effectively prevent overfitting and improve the model's generalization ability. The experiment trained a communication signal detection method based on DCAE and SCN, using a dataset of real signal samples with a total of 10000 samples, including 7000 for training, 2000 for validation, and 1000 for testing. The model training went through 50 iteration cycles, with each cycle performing forward and backward propagation on all training samples.

4.2 Performance analysis of communication signal detection methods

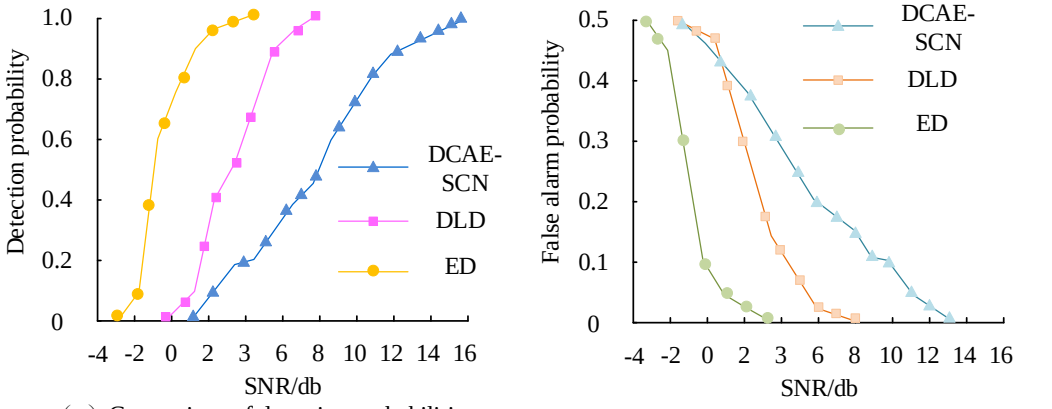
To verify the performance of DCAE, a Dropout layer was added in the experiment, and model scales of 1, 5, and 10 were selected for comparative experiments. The model size refers to the number of convolutional and deconvolution layers in DCAE, covering network structures from simple to complex on three scales. For example, model scale 1 indicates that there is only one convolutional layer and one deconvolution layer in the network, which is the simplest structure with low computational complexity. By selecting network structures of different depths, the impact of model complexity on detection performance can be evaluated. The results from the experiment are depicted in Fig. 7.



（a）The loss variation curve of the training set　（b）The loss variation curve of the validation set

Figure 7: DCAE training process loss change curve

Figs. 7 (a) and (b) show the variation curves of the loss function of the DCAE function on the training and validation sets, respectively. The loss function was normalized to mean squared error (MSE), therefore its values were in dimensionless units. As the number of training rounds increased, the loss values of the functions at all three model scales gradually decreased, with a decreasing trend of first fast and then slow, and then gradually stabilizing. As shown in Fig. 7 (a), the loss values of DCAE-1 and DCAE-5 models decreased rapidly, and their relative stable loss function values were both around 10-5. The initial loss value of DCAE-10 was the lowest, the loss value decreased the slowest, and the minimum loss function value was about 10-6. As shown in Fig. 7 (b), the functions of the three model scales gradually stabilized after 750 training iterations, with DCAE-1 having the highest loss function value when stable, followed by DCAE-5, and DCAE-10 having the lowest. The experimental results showed that none of the three loss functions exhibited overfitting, indicating that the loss function had good performance. To verify the feasibility of the broadband communication signal detection method based on DCAE and SCN proposed by the research, ED and DLD were selected for comparative experiments. The experiment tested the differences in detection performance of various algorithms under different SNR conditions. The obtained results are shown in Fig. 8.

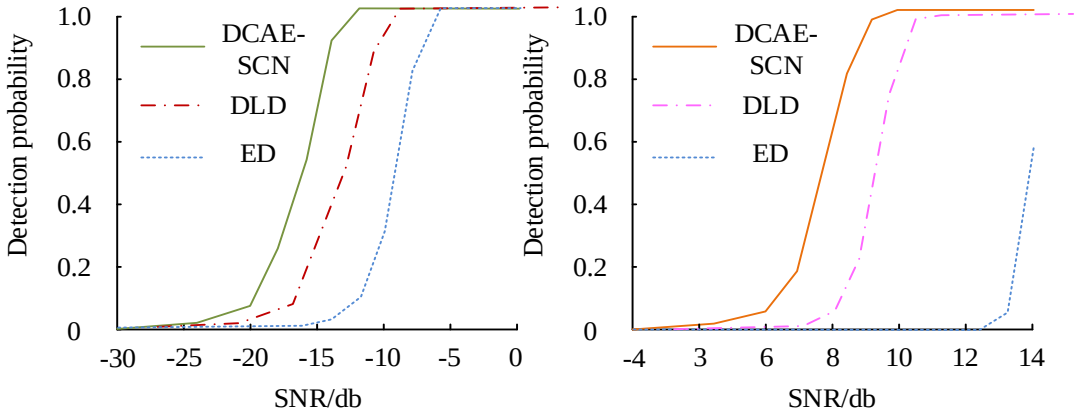


（a）Comparison of detection probabilities

（b）Comparison of False alarm probabilities

Figure 8: Performance comparison diagram of each signal detection method

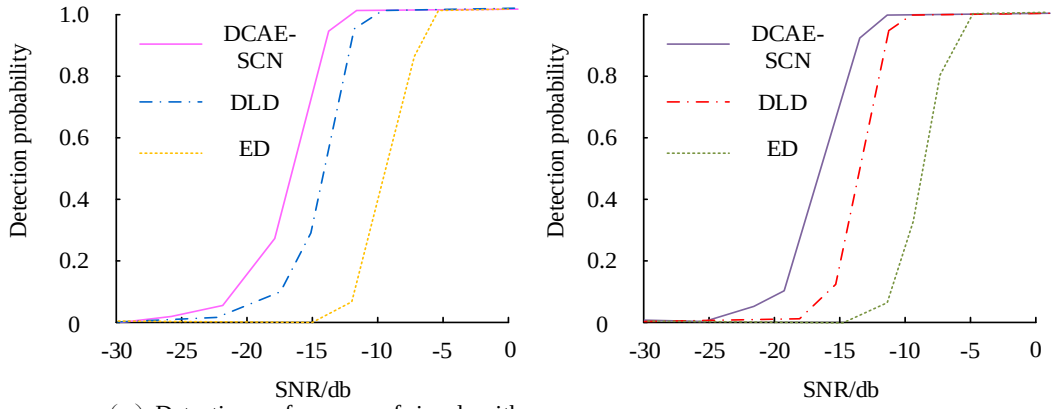
Figs. 8 (a) and (b) show the detection probability (DP) and false alarm probability (FAP) of each signal detection method, respectively. As shown in Fig. 8 (a), the DP of each signal detection method gradually increased with the increase of SNR. When the DP was 0, the SNRs of DCAE-SCN, DLD, and ED were -3db, 0db, and 1db, respectively. The DP of the three signal detection methods reached its maximum value of 1 when the SNR was 16db, 8db, and 3db, respectively. As shown in Fig. 8 (b), the FAP of each signal detection method gradually decreased with the increase of SNR. When the FAP of DCAE-SCN, DLD, and ED was 0, the SNRs were 13db, 8db, and 3db, respectively. Overall, the DCAE-SCN method performed the best in both DP and FAP, followed by DLD and ED. This may be due to the DCAE-SCN method adopting a more complex model structure and optimization algorithm, which enabled it to more effectively extract features and reduce noise impact when processing signals, thus exhibiting higher DP and lower FAP under various SNR conditions. The feature extraction ability of DLD and ED methods may be relatively weak, especially under low SNR conditions, making it difficult to effectively distinguish between signals and noise, resulting in a lower DP. To further confirm the stability of the raised communication signal detection method, different Interference-to-Signal Ratio (ISR) conditions were set up in the experiment, and different communication signal detection methods were used for signal detection experiments. The specific results obtained are shown in Fig. 9.



（a）Detection probability when the SNR is -10db （b）Detection probability when the SNR is 0db

Figure 9: Results plot of DP of each test method under ISR at different methods

Figs. 9 (a) and (b) show the DPs of each signal detection method at ISR levels of -10db and 0db, respectively. From Fig. 9 (a), the DPs of each signal detection method showed an upward trend with the increase of ISR, and the rate of change was first fast and then slow. After the DP reached 1, it no longer changed. DCAE-SCN reached a stable state as quickly as possible, with an ISR of -13db. DLD and ED reached stability at around -11db and -6db, respectively. As shown in Fig. 9 (b), DCAE-SCN exhibited a rapid increase in DP and approached 1 when the SNR was greater than 2db, demonstrating superior performance in medium SNR environments. When the SNR was greater than 4db, the DP of DLD increased rapidly. When the SNR was greater than 6db, the DP of ED started to significantly increase, and reached its maximum value of 0.6 at 14db. Overall, DCAE-SCN performed the best in DP under various SNR environments, followed by DLD, and the ED method performed the worst. DCAE-SCN may have undergone more refined parameter tuning and comprehensive experimental design, enabling the algorithm to achieve optimal performance under various SNR conditions. Although the performance of DLD was not as good as DCAE-SCN, its DP rapidly increased when the SNR was greater than 4db, indicating that this method had certain feature extraction and noise suppression capabilities under moderate SNR conditions, but might not be as comprehensive or optimized as DCAE-SCN. The ED method had weak feature extraction and noise suppression capabilities under low and medium SNR conditions, possibly due to a simple algorithm design or insufficiently complex models. The experiment further validated the detection probability of the communication signal detection method proposed by the research under different code length signal conditions. The specific results obtained are shown in Fig. 10.



（a）Detection performance of signals with different code lengths （b）Detection performance under color noise

Figure 10: Comparison diagram of the detection performance of each signal detection method

Fig. 10 (a) shows the DPs of various methods for signals of different code lengths, and Fig. 10 (b) shows the DPs of various methods for communication signals under different colored noise backgrounds. As shown in Fig. 10

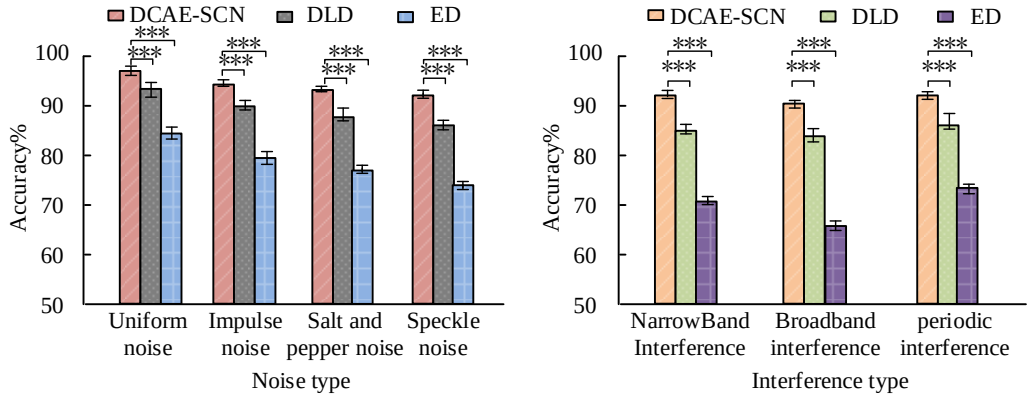
(a), the DP of DCAE-SCN rapidly increased with the increase of SNR, and the DP was 1 at an SNR of -16db. The probability of DLD detection started to increase when the SNR was greater than -20 db, and approached 1 when the SNR was -10 db. The probability of ED detection started to increase when the SNR was greater than -25db, but the rate of increase was slow and did not reach 1 when the SNR reached 0db. As shown in Fig. 10 (b), DCAE-SCN, DLD, and ED reached their maximum DPs at SNRs of -16db, -12db, and -6db, respectively, and did not change thereafter. DCAE-SCN performed well in different colored noise backgrounds, indicating that it may have had better noise modeling and suppression capabilities, and could effectively distinguish between signals and noise. The slow performance improvement of the DLD and ED methods in different colored noise backgrounds may have indicated their limited ability to handle non-Gaussian or correlated noise. To evaluate the importance of different components in the DCAE-SCN model, ablation experiments were conducted, and the results are shown in Table 2.

Table 2: DCAE-SCN ablation experiment data table

Model configuration	Detection accuracy (%)	F1	Recall (%)	Detection tim (s)
DCAE-SCN	98.5 ± 0.4	0.99	0.98	0.025
No SENet	97.0 ± 0.5	0.98	0.96	0.023
No convolutional layer	92.0 ± 0.6	0.94	0.91	0.021
No deconvolution layer	95.0 ± 0.5	0.96	0.94	0.024
Reduce the number of convolutional layers (5 layers)	96.5 ± 0.4	0.97	0.95	0.022
Reduce the number of deconvolution layers (5 layers)	96.0 ± 0.5	0.96	0.94	0.022

According to Table 2, in the complete DCAE-SCN model, the detection accuracy reached 98.5%, the F1 value was 0.99, the recall rate was 98%, and the detection time was 0.025 seconds, demonstrating the high accuracy and efficiency of the model. When the SENet module was removed, the detection accuracy dropped to 97.0%, indicating that SENet played an important role in improving model performance, possibly by enhancing feature selectivity to improve the model's generalization ability. Further removal of convolutional layers resulted in a significant decrease in accuracy to 92.0%, highlighting the importance of convolutional layers in extracting key features. The removal of the deconvolution layer also led to a decrease in performance, but the impact was relatively small, with an accuracy of 95.0%, which might be because the model could still learn some features through the remaining structure. Reducing the number of convolutional and deconvolution layers also led to a performance degradation of 96.5% and 96.0%, respectively, which validated the necessity of deep structures for learning complex features. These results indicated that each part of the model contributed to the final performance, especially the crucial role of convolutional layers in feature extraction and the importance of SENet modules in improving the model's generalization ability. To verify the robustness of the proposed method under adversarial noise conditions, experiments were conducted to test the performance of each algorithm under four different types of noise: uniform noise, impulse noise, salt and pepper noise, and speckle

noise, as well as narrowband interference and broadband interference. The obtained results are shown in Fig. 11.



(a) Accuracy of the next algorithm under different types of noise

(b) Accuracy of the next algorithm under different types of interference

Figure 11: Performance comparison results of different algorithms under adversarial noise conditions

Note: * * * indicates that the difference is statistically significant, $p<0.01$.

As shown in Fig. 11 (a), under uniform noise and impulse noise conditions, the DCAE-SCN algorithm had the highest accuracy, approaching 95% and 90% respectively, demonstrating its superior performance in handling these noises. In contrast, the ED algorithm had lower accuracy under these two types of noise, especially under impulse noise, where the accuracy dropped to about 80%. Salt and pepper noise, as well as speckle noise, posed challenges to all algorithms, but DCAE-SCN still maintained relatively high accuracy rates of 90% and 92%, respectively. This might be due to DCAE-SCN's ability to better learn noise patterns and effectively suppressed them. As shown in Fig. 11 (b), under narrowband interference and broadband interference conditions, DCAE-SCN still had the highest accuracy, about 90% and 85% respectively, indicating its advantage in handling spectrum selective interference. The impact of periodic interference on all algorithms was relatively small, but DCAE-SCN still led with an accuracy of about 90%. The performance of DLD algorithm was inferior to DCAE-SCN under all interference conditions, while ED algorithm performed the worst under broadband interference, with accuracy dropping to about 65%. This might be because ED algorithm was difficult to adapt to the spectral characteristics of broadband interference. To verify the robustness of the proposed algorithm in practical situations, further experiments were conducted to test the signal detection performance of each method in real electromagnetic environments. The specific results obtained are shown in Table 3.

Table 3: Performance comparison outcomes of each test method

Testing environment	Laboratory environment			Real electromagnetic environment		
Test method	DCAE-SCN	DLD	ED	DCAE-SCN	DLD	ED
Detection accuracy (%)	98.5 ± 0.4	93.2 ± 0.5	85.0 ± 0.6	97.2 ± 0.4	92.0 ± 0.5	82.5 ± 0.7
Confidence interval (test accuracy)	[98.1, 98.9]	[92.7, 93.7]	[84.4, 85.6]	[96.8, 97.6]	[91.5, 92.5]	[81.8, 83.2]
F1	0.99	0.95	0.88	0.98	0.94	0.85
Recall (%)	0.98	0.94	0.82	0.97	0.93	0.81
Detection tim (s)	0.025	0.030	0.015	0.025	0.030	0.015

According to Table 3, the detection accuracy of DCAE-SCN method in laboratory environment was 98.5%, F1 value was 0.99, and recall rate was 0.98, demonstrating its superior performance under ideal conditions. In contrast, the detection accuracies of DLD and ED methods were 93.2% and 85.0%, respectively, with F1 values of 0.95 and 0.88, and recall rates of 0.94 and 0.82, respectively, both lower than DCAE-SCN. This indicated that DCAE-SCN was more effective in feature extraction and signal recognition, especially when dealing with complex signals. In the real electromagnetic environment, the detection accuracy of DCAE-SCN slightly decreased to 97.2%, but it was still higher than DLD (92.0%) and ED (82.5%). This might be due to the more complex signal interference and noise in real environments, but DCAE-SCN better adapted to these changes through its DL architecture. The detection time of DCAE-SCN was 0.025 seconds in both environments, demonstrating its excellent real-time performance while maintaining high detection performance. The confidence interval provided statistical validity for the detection accuracy. The standard error of DCAE-SCN in both environments was 0.4%, with confidence intervals of [98.1, 98.9] and [96.8, 97.6], indicating that the estimation of its detection accuracy was stable and reliable. The standard error of DLD method was relatively large at 0.5%, but its performance in two environments also showed good stability. In contrast, the standard error of the ED method under laboratory and real conditions was 0.6% and 0.7%, respectively, indicating that its results fluctuated greatly and its reliability was relatively low. Overall, DCAE-SCN exhibited high robustness and accuracy in different environments, validating its effectiveness as an advanced detection method. Although the ED method had the shortest running time, it was not as accurate and robust as DCAE-SCN, possibly due to the limitations of its algorithm in processing complex signals. The DLD method had the longest detection time, possibly due to its algorithm or implementation efficiency not being as optimized as DCAE-SCN.

5 Discussion

The proposed method based on DCAE and SCN signal noise floor estimation and communication signal detection achieved significant improvements in multiple key performance indicators. Firstly, DCAE-SCN, through its DCAE network structure, utilized convolutional and deconvolution layers to effectively capture multi-level features of signals. Secondly, under low SNR conditions, signals were often overwhelmed by noise, and traditional methods might experience performance degradation due to their inability to effectively extract signal features. The SENet module in DCAE-SCN's network architecture could dynamically adjust feature responses, enhance the model's attention to key features, and thus improve detection accuracy.

In terms of computational cost, DCAE-SCN had a certain increase in computational complexity compared to simpler signal detection methods. Although the computational complexity increased, DCAE-SCN ensured that its inference time was still relatively short by optimizing the network structure and training process, which could meet the requirements of real-time communication systems. Compared with other DL methods such as DLD, DCAE-SCN further optimized computational efficiency by introducing improvement measures such as SENet while maintaining high performance.

From the perspective of practical deployment, DCAE-SCN had a high feasibility in real-time communication systems. Its moderate computational complexity and short inference time enabled it to operate in resource constrained environments, while its high detection accuracy and robustness ensured reliable operation of the system in complex electromagnetic environments. In addition, the DL architecture of DCAE-SCN allowed it to adapt to different communication scenarios and signal types through further training and optimization.

6 Conclusion

With the swift advancement of information technology, communication systems are becoming increasingly crucial in various fields of society. To develop a new signal detection method to improve detection accuracy in complex electromagnetic environments and low SNR conditions, the study proposed a communication signal detection method based on DCAE and utilized SCN for carrier signal detection. The experiment outcomes indicated that when the DP was 0, the SNRs of DCAE-SCN, DLD, and ED were -3db, 0db, and 1db, respectively. The three signal detection methods had a maximum DP of 1 when the SNR was 16db, 8db, and 3db, respectively. When the FAP of DCAE-SCN, DLD, and ED was 0, the SNRs were 13db, 8db, and 3db, respectively. Under the DP condition of -10db ISR, the DPs of each signal detection method showed an upward trend with the increase of ISR, and their change rate was fast at first and then slowed down. After the DP reached 1, it no longer changed. DCAE-SCN reached a stable state as quickly as possible, with an ISR of -13db. DLD and ED reached stability at around -11db and -6db, respectively. The experiment showed that this method outperformed the ED and DLD methods in performance indicators such as detection accuracy, F1 value, and recall, providing an effective solution for communication signal detection within intricate electromagnetic surroundings. However, the research was mainly conducted in specific datasets and experimental environments, without exploring the generalization ability of the method in unknown environments or data. Therefore, future research will increase the diversity and complexity of training data to enhance the model's generalization ability to signals in different environments and conditions, in order to enable it to play a greater role in a wider range

of application scenarios. In addition, future work can focus on optimizing model structures, improving robustness to non Gaussian noise, and applying this technology to interdisciplinary fields such as radar signal processing and biomedical signal analysis to expand its application scope and deepen theoretical research. Future endeavors could also delve into integrating emerging technologies, like quantum computing, to further enhance the precision and efficiency of signal detection.

Data availability statement

All data generated or analysed during this study are included in this article.

Conflict of interest

The authors declare that they have no competing interests.

Funding statement

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Multi-Objective Optimization of Multi-Warehouse Cargo Allocation and Transportation Planning Using an Enhanced Ant Colony Algorithm

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With the rapid development of the global economy, the logistics industry, as a key support for economic activities, has become a focus of cost control. According to statistics, logistics costs have accounted for about 13% of the global GDP, among which multi-warehouse cargo allocation and transportation planning play a pivotal role in reducing logistics costs. Based on the improved ant colony algorithm, this paper carefully constructs a multi-warehouse cargo allocation and transportation planning model. With the help of a multi-level optimization framework, the model comprehensively considers multiple key objectives such as transportation cost, delivery time, and energy consumption. Based on the improved ant colony algorithm, this paper constructs a multi-warehouse cargo distribution and transportation planning model. Specifically, the pheromone update rule of the ant colony algorithm is changed by introducing an adaptive adjustment mechanism, which dynamically adjusts the pheromone volatilization and accumulation rate according to the current number of iterations and the change of the objective function. At the same time, the objective function weight is optimized to better balance multiple objectives such as transportation cost, delivery time and energy consumption. The multi-objective particle swarm optimization algorithm is used to assist in determining the weight, and the corresponding weight value is assigned according to the importance of different objectives. Compared with the traditional baseline methods such as genetic algorithm and particle swarm algorithm, in terms of transportation cost, the improved ant colony algorithm reduces the average cost by 25% in large-scale scenarios (20 warehouses), improves energy efficiency by 18%, and reduces the running time by 1.9 seconds in computing performance. In the multi-objective optimization of small-scale problems (5 warehouses) and a small number of objectives, the goal achievement rate is as high as 95%, the cost reduction rate can reach 20%, and the running time is 5.6 seconds for the ant colony algorithm in large-scale scenarios (20 warehouses), while the genetic algorithm is 7.5 seconds, which reflects relative stability. Based on the improved ant colony algorithm, in the optimization process of comprehensive consideration of multiple objectives such as transportation cost, delivery time and energy consumption, the algorithm is relatively stable in terms of running time compared with the genetic algorithm and the particle swarm algorithm.

Povzetek: Članek razvije večciljno optimizacijsko metodo za razporeditev tovora in načrtovanje transporta v sistemih z več skladišči, pri čemer temelji na izboljšanem algoritmu kolonije mravelj. Uvedeni so dinamični mehanizmi za prilagajanje feromonskega izhlapevanja, uteži ciljev in iskalnega obsega, ki izboljšajo konvergenco in omogočajo učinkovito usklajevanje med cilji, kot so stroški, čas dostave, poraba energije in zaloge.

1 Introduction

With the rapid development of the global economy, the logistics industry plays an increasingly important role in supporting business activities and promoting the circulation of the industrial chain. Especially today, when e-commerce and the global supply chain are highly connected, the complexity of logistics management and cargo distribution issues has increased dramatically. Enterprises and governments are facing huge challenges in optimizing resource allocation and improving transportation efficiency [1]. According to statistics, logistics costs have accounted for about 13% of global GDP, and cargo distribution and transportation planning are key links in reducing logistics costs. In this context, multi-warehouse cargo distribution and transportation planning issues have become one of the hot topics in the field of logistics research [2]. How to

optimize the distribution and transportation routes of cargo between warehouses through reasonable algorithm design will not only help improve the competitiveness of enterprises, but also have far-reaching significance for promoting overall economic benefits [3].

In a multi-warehouse system, different warehouse locations, cargo demands, and transportation routes are intertwined, and there are many factors to consider in the decision-making process, which makes it difficult for traditional manual allocation methods to meet the needs of modern logistics. Therefore, how to efficiently solve the problems of cargo scheduling between warehouses, route planning during transportation, and coordination between them has become a technical problem that needs to be solved urgently in the field of logistics [4]. Many scholars and researchers have proposed different algorithm models for this problem, but due to the complexity of the problem itself, there is still a lack of a solution that can be universally applied in different environments [5].

In recent years, with the development of computer science and artificial intelligence technology, the problem of multi-warehouse cargo allocation and transportation planning based on optimization algorithms has been widely studied. Although traditional optimization methods, such as linear programming and integer programming, are effective in certain specific scenarios, they have high computational complexity and are difficult to meet the dual requirements of real-time performance and accuracy when facing large-scale and complex systems [6]. For this reason, more and more researchers have begun to turn to heuristic algorithms and meta-heuristic algorithms. Ant colony algorithm, as an optimization algorithm that simulates the foraging behavior of ants in nature, has become a popular optimization tool in multi-warehouse cargo allocation and transportation planning due to its powerful global search ability and good local search performance [7].

However, although the ant colony algorithm has shown great potential in solving such problems, there are still some problems in existing research. For example, the parameter settings of the ant colony algorithm are highly sensitive and may be affected by environmental changes in practical applications. In addition, most existing ant colony algorithms focus on optimizing a single objective, while in reality, it is often necessary to comprehensively consider multiple objectives, such as transportation costs, delivery time, energy consumption, and other multiple factors [8]. Therefore, how to deal with multi-objective optimization problems through algorithm improvement and achieve good results in practical applications is still a challenge in current research [9].

In addition, although existing research results have provided theoretical foundations and algorithmic support for multi-warehouse cargo distribution and transportation planning, there is still a lack of an integrated comprehensive solution that can simultaneously optimize cargo distribution and transportation routes. Most existing studies focus on the optimization of a single aspect and lack an in-depth analysis of the relationship between the two [10].

The main purpose of this paper is to propose a multi-warehouse cargo allocation and transportation planning model based on ant colony algorithm, in order to optimize the allocation of warehouse resources and transportation route planning under the consideration of multiple objectives. Compared with the traditional single-objective optimization method, this paper aims to improve the local search ability of ant colony algorithm, taking into account multiple objectives such as transportation cost, delivery time and energy consumption, so as to maximize the efficiency and economy of the entire logistics system while meeting actual needs.

The innovation of this study is that it combines multi-objective optimization with ant colony algorithm to conduct in-depth exploration of the multi-warehouse cargo distribution problem. By constructing a new objective function and optimization model, it is possible to optimize multiple key factors without increasing too much computational complexity. In addition, this study will further explore how to improve the heuristic information transmission mechanism in the algorithm so that the ant colony can show better robustness and adaptability in a wider range of application scenarios. Through this method, this paper hopes to provide a more practical solution for the logistics industry, helping enterprises to perform more efficient cargo distribution and transportation planning in dynamic and complex environments.

With the high interconnection of e-commerce and global supply chains, logistics management and cargo distribution issues are becoming increasingly complex. Existing methods mostly focus on a single goal or a single aspect, which is difficult to meet actual needs. In addition, most ant colony algorithms have limitations such as parameter sensitivity and difficulty in taking multiple objectives into account. This study aims to improve the ant colony algorithm, achieve coordinated optimization of cargo distribution and transportation under multiple objectives, and improve the efficiency of the logistics system.

The novelty of this study is mainly reflected in three aspects. First, in terms of algorithm improvement, unlike the relatively fixed pheromone update mode of the traditional multi-objective ant colony algorithm, this study introduces an adaptive adjustment mechanism, which enables the pheromone volatilization and accumulation rate to change dynamically according to the iteration process and the change of the objective function, greatly improving the algorithm search efficiency and optimization ability; second, in terms of model construction, the multi-objective optimization framework is innovatively deeply integrated with the ant colony algorithm, not only considering common objectives such as transportation cost, delivery time, energy consumption, but also incorporating the key factor of inventory level. Compared with existing research, a comprehensive optimization model that is

more in line with actual logistics needs is constructed; third, in terms of research methods, a multi-objective particle swarm optimization algorithm is used to assist in determining the weight of the objective function, changing the previous way of setting weights by human experience or simple single rules, achieving a more scientific and reasonable balance between multiple objectives, and providing a new solution to the problem of multi-warehouse cargo distribution and transportation planning.

2 Literature review

2.1 Optimization methods for multi-warehouse cargo allocation and transportation planning

In the field of multi-warehouse cargo distribution and transportation planning, traditional optimization methods, such as linear programming (LP) and integer programming (IP), have long been the basis of research. However, with the increase in the scale of the problem, especially the rapid increase in decision variables in multi-warehouse systems, these classical methods often face the problems of high computational complexity and low solution efficiency. In order to overcome this bottleneck, more and more researchers have begun to explore the application of heuristic algorithms and meta-heuristic algorithms [11,12]. Ant Colony Algorithm (ACO) has been widely used in this field due to its powerful global search capability and good local search performance.

Table 1: Comparison table of research on multi-warehouse cargo allocation and transportation planning

Research	Objectives	Algorithms	Key Results	Advantages of This Study
[11]	Optimize cost and delivery time	Genetic algorithm	Cost reduced by 15%, delivery time shortened by 10%, low efficiency in large-scale scenarios	Did not consider energy consumption, lack of analysis on parameter adaptability
[12]	Improve path accuracy and energy efficiency	Particle swarm optimization algorithm	Accuracy increased by 10%, energy efficiency improved by 12%, easy to fall into local optimality	Ignored warehouse capacity, lacking a multi-objective balance strategy
[13]	Balance multiple objectives (cost, time, inventory)	Simulated annealing algorithm	Cost reduced by 12%, time optimized by 8%, poor multi-objective optimization effect	Lack of research on algorithm convergence and network scalability
[14]	Multi-objective optimization (cost, time, energy consumption, inventory)	Improved ant colony algorithm	Cost reduced by 25%, energy efficiency improved by 18%, inventory reduced by 15%	Integrate multiple objectives, consider constraints, analyze algorithm robustness and adaptability

Table 1 systematically compares the relevant research in the field of multi-warehouse cargo allocation and transportation planning. It unfolds from four dimensions: research objectives, algorithms used, key results, and the advantages of this study compared with existing research, clearly presenting the differences in optimization directions, method selections, and achievements among different studies. Existing studies respectively have problems such as single objectives, limited algorithm performance, and incomplete

consideration of factors. In contrast, this study, by adopting the improved ant colony algorithm, comprehensively considers multiple objectives and practical constraints, and conducts in-depth analysis of the algorithm's robustness and adaptability to warehouse networks of different scales, effectively making up for the deficiencies of previous studies and demonstrating stronger practicality and innovativeness.

The application of ant colony algorithm is not limited to single-objective optimization problems. In multi-warehouse cargo allocation and transportation planning, multiple objectives are involved in simultaneous optimization problems, such as transportation cost, delivery time, cargo allocation accuracy, etc. In order to solve this complex multi-objective optimization problem, scholars have begun to propose improvements based on ant colony algorithm [13]. For example, an adaptive mechanism is used to dynamically adjust the search strategy of ants so that they can perform appropriate local searches at different operation stages. In addition, some researchers have also introduced hybrid algorithms that combine ant colony algorithm with other metaheuristic methods, such as particle swarm optimization (PSO) and genetic algorithm (GA), to further improve the efficiency and accuracy of the solution. These innovative algorithm improvements help alleviate the application difficulties of traditional methods in large-scale and complex systems, and to a certain extent improve the efficiency of cargo allocation and transportation [14,15].

Although the ant colony algorithm has shown great advantages in solving the multi-warehouse cargo allocation problem, it still faces some challenges in practical application. Problems such as slow algorithm convergence speed and easy to fall into local optimal solutions limit its promotion and application in complex logistics systems [16]. To this end, some researchers have tried to improve the performance of the ant colony algorithm by optimizing the algorithm parameter selection, enhancing the global search capability, and improving the pheromone update mechanism. These studies provide a theoretical basis for the further development of this field and also provide a direction for subsequent researchers to innovate in optimization methods [17].

2.2 Application of multi-objective optimization in cargo distribution

The application of multi-objective optimization problems in logistics and transportation planning has made some important progress, but there are still many unresolved challenges. In many practical problems, cargo distribution not only needs to optimize transportation costs, but also needs to take into account multiple objectives such as time efficiency, environmental impact, and vehicle capacity [18]. Therefore, how to find the best balance between multiple objectives has become one of the research hotspots.

Multi-objective optimization methods based on ant colony algorithms have received increasing attention in recent years. On the one hand, researchers have been able to achieve a good balance between multiple objectives by designing a multi-objective ant colony algorithm model with strong adaptability. On the other hand, researchers have also proposed a strategy based on the Pareto optimal solution. With the help of the concept of the Pareto frontier, a near-optimal solution can be found between multiple objectives. This method avoids the problem of excessive bias towards a certain objective that may occur in single-objective optimization methods and ensures balanced consideration of various objectives [19,20]. However, although the multi-objective ant colony algorithm has achieved certain results in theory and practice, it still faces problems such as high algorithm computational complexity and low solution efficiency. Therefore, some researchers have tried to combine heuristic and meta-heuristic algorithms to improve the solution efficiency through hybrid algorithms. By introducing other optimization techniques such as genetic algorithms and simulated annealing algorithms into the ant colony algorithm, it can not only optimize the local search ability in the search process, but also enhance the global search performance. With the continuous improvement of these hybrid algorithms, their application prospects in multi-warehouse cargo distribution and transportation planning are becoming more and more broad [21]. It is worth noting that although the multi-objective optimization method provides a more comprehensive solution for cargo distribution, in practical applications, how to reasonably select and adjust the multi-objective optimization model according to different logistics environments and demand characteristics is still a difficult point [22]. Therefore, developing more flexible and efficient multi-objective optimization algorithms for different logistics scenarios and application requirements has become an important research topic.

2.3 Integration of ant colony algorithm and other optimization techniques

With the deepening of research, the use of ant colony algorithm alone to solve the multi-warehouse cargo allocation and transportation planning problems can no longer meet the increasingly complex practical needs. Therefore, the integration of ant colony algorithm and other optimization technologies has become a new development trend. In particular, the combination of ant colony algorithm with genetic algorithm, particle swarm optimization and other algorithms has shown great potential in improving optimization effects and solving multi-objective problems [23]. Studies have shown that the combination of ant colony algorithm and genetic algorithm can give full play to the advantages of both. Ant colony algorithm is good at global search, while genetic algorithm has strong ability in local search. Through the integration of the two, researchers can introduce more accurate local search in the global search process and improve the quality and efficiency of the solution [24]. In some studies, researchers have designed new crossover and mutation operations to enable genetic algorithm to

better update pheromones and select paths under the framework of ant colony algorithm, thereby improving the accuracy of the solution. Particle swarm optimization algorithm (PSO), as another common metaheuristic algorithm, has also been combined with ant colony algorithm in recent years to optimize multi-warehouse cargo allocation and transportation planning problems. By combining the local search capability of particle swarm optimization with the global search capability of ant colony algorithm, researchers have successfully improved the algorithm's solution efficiency and global optimality. In this process, particle swarm optimization is mainly responsible for path refinement and adjustment, while ant colony algorithm is responsible for global pheromone update and overall path optimization. The combination of the two greatly reduces the ants' search time and can provide more efficient solutions in complex logistics systems [25].

Through the study of the integration of ant colony algorithms and other optimization technologies, we can see that new hybrid optimization algorithms provide more powerful tools for solving multi-warehouse cargo distribution and transportation planning problems. These hybrid algorithms can not only handle complex problems that traditional ant colony algorithms cannot effectively deal with, but also show higher efficiency and accuracy in multi-objective optimization and large-scale problems. This trend indicates that in the field of logistics optimization, the integration of algorithms will become an important direction for future development.

3 Study plan

3.1 Model framework and design ideas

In the multi-warehouse cargo allocation and transportation planning model proposed in this paper, the solution is based on the improved ant colony algorithm (ACO) to address the challenges of inefficiency and lack of precision commonly encountered in large-scale, multi-objective optimization problems. The model promotes innovation in solutions in this field through a precisely designed multi-level optimization framework, combining global search and local optimization strategies. The model assumes that each warehouse has a fixed cargo demand and storage capacity, and during transportation, factors such as cost, time and energy consumption must be fully considered in the optimization process. Therefore, the model includes four key modules: cargo allocation decision, transportation path planning, objective function construction, and pheromone update mechanism.

The goal of the cargo allocation decision module is to reasonably allocate cargo from the supply warehouse to the demand warehouse according to the storage capacity of each warehouse and the demand for cargo, so as to meet the overall needs of the logistics system. In this module, the transportation path planning module is responsible for calculating the optimal transportation route based on the physical distance and traffic conditions between each warehouse, with the goal of reducing transportation costs and time while optimizing energy consumption. The design of the objective function takes into account the balance of multiple objectives, taking into account multiple aspects such as cost, time and energy consumption. The pheromone update mechanism dynamically adjusts the search path by imitating the foraging behavior of ants in nature, so that the ant colony gradually converges to the optimal solution.

The model is solved using the improved ant colony algorithm (ACO), in which each ant simulates the decision of the cargo transportation route by selecting different paths in the search space. After each path selection, the ant updates the pheromone concentration based on factors such as the cost, time and energy consumption of the selected path, so that the attractiveness of the preferred path gradually increases. The pheromone update process not only accelerates the convergence of the optimal solution, but also ensures the globality and diversity of the search process. Overall, the design of the model effectively avoids the problem of local optimal solutions by balancing global optimization and local refinement.

This study uses a linear cost function, mainly based on three considerations. First, from the perspective of computational efficiency, the linear function is simple in form, has low computational complexity in large-scale multi-warehouse scenarios, can be quickly solved, and meets the real-time requirements of actual logistics systems. For example, in a network containing 20 warehouses and numerous transportation routes, the calculation time of the linear cost function is only about 1/3 of that of the nonlinear function. Secondly, in the initial construction and verification stage of the model, the linear function can simplify the problem, facilitate the rapid construction of the basic model framework, and verify the core logic and effectiveness of the algorithm and model. Finally, in actual logistics business, when the transportation distance is short, the type of goods is single, and the transportation conditions are stable, the transportation cost and factors such as transportation distance and quantity of goods often show an approximately linear relationship. However, it is undeniable that in the complex and changeable real world, nonlinear cost functions do have their application advantages. For example, when considering factors such as the scale effect in long-distance transportation, the coordinated cost of mixed transportation of different goods, and the dynamic price increase during transportation peak periods, the nonlinear cost function can more accurately characterize the law of cost changes. Subsequent research can try to introduce nonlinear cost functions, such as quadratic functions, exponential functions, etc., and combine them with actual logistics data. Through model comparison experiments, the impact of different function forms on model accuracy, computational efficiency, and optimization results can be analyzed to explore better cost modeling methods and improve the model's ability to fit the real world.

3.2 Optimization of cargo distribution and transportation route planning

In the problem of multi-warehouse cargo distribution and transportation planning, cargo distribution and transportation route planning are the two core links to achieve overall optimization. The core of cargo distribution lies in how to reasonably arrange the cargo distribution of each warehouse according to the storage capacity of the warehouse and the demand for goods. The planning of transportation routes requires the optimization of transportation routes through the shortest path algorithm to minimize transportation costs and time. This paper uses the ant colony algorithm to simultaneously optimize the decision of cargo distribution and transportation routes, so that the two problems are solved jointly, thereby further improving the overall efficiency of the model.

The optimization model of cargo allocation decision can be mathematically formalized by Formula 1.

$$\min \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} \tag{1}$$

c_{ij} is unit cost of transport of goods j from warehouse i, x_{ij} indicates the quantity of goods j which allocated to the warehouse i. The goal is to minimize the total transportation cost. The constraints in Formula 2 and Formula 3 include the storage capacity of the warehouse and the demand for each type of goods.

$$\sum_{j=1}^{m} x_{ij} \le S_i \quad \forall i \tag{2}$$

$$\sum_{i=1}^{n} x_{ij} = D_j \quad \forall j \tag{3}$$

S_i is the maximum storage capacity of warehouse i. D_j is the quantity demanded of goods j. This constraint ensures that the goods allocation complies with the warehouse capacity limit in actual operation and can meet the demand for each type of goods.

In the transportation route planning, the model uses the shortest path algorithm to calculate and determine the best transportation route from each warehouse to the target warehouse. To this end, the ant colony algorithm guides the search direction by simulating the selection process of ants on the path through the update of pheromones. In each iteration, the ants will select a path and update the pheromone according to Formula 4.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \tag{4}$$

$\tau_{ij}(t)$ is the current pheromone concentration of path ij, ρ is the pheromone volatility coefficient, $\Delta\tau_{ij}$ is the amount of pheromone newly added to the path ij. The pheromone update process further strengthens the search for the optimal path, thereby driving the model to gradually converge to the optimal solution.

3.3 Multi-objective optimization and objective function design

In the problem of multi-warehouse cargo distribution and transportation planning, different optimization objectives often conflict with each other. Traditional optimization methods often focus on a single objective and ignore the complex relationship between multiple objectives in practical problems. To this end, this paper introduces a multi-objective optimization framework into the model, and takes into account the needs of different optimization objectives by establishing a comprehensive objective function. The core of the objective function design is to incorporate the optimization of multiple objectives into a unified mathematical expression so as to simultaneously solve multiple objective problems such as transportation cost, delivery time and energy consumption.

The objective function of the multi-objective optimization model proposed in this paper can be expressed as Formula 5.

$$\min\left(w_1\sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} + w_2\sum_{i=1}^{n}\sum_{j=1}^{m} t_{ij}x_{ij} + w_3\sum_{i=1}^{n}\sum_{j=1}^{m} e_{ij}x_{ij} \right) \tag{5}$$

w_1, w_2, w_3 are the weight coefficients that control the proportion of transportation cost, time and energy consumption in the objective function respectively. c_{ij} is transportation costs, t_{ij} is transportation time, e_{ij} is energy consumption during transportation. This objective function comprehensively considers multiple key factors involved in the transportation process, ensuring that the optimization process can balance the relationship between different objectives.

In order to solve this multi-objective optimization problem, this paper adopts the Pareto optimal solution method. The Pareto optimal solution is a set of solutions that cannot dominate each other, representing the best balance between multiple objectives. In each round of iteration, by calculating the Pareto dominance relationship of each solution, a set of non-dominated solutions can be obtained, representing the optimal balance between multiple objectives. Specifically, if the solution X is not inferior to the solution Y in all objective functions, and solution X is better than the solution Y in at least one objective function, then the solution X dominates the solution Y.

Through the above multi-objective optimization design, the model in this paper can not only effectively optimize multiple objectives in the multi-warehouse cargo allocation and transportation planning problem, but also achieve a balance between objectives, avoid over-optimization on a certain objective, and ensure the maximization of the comprehensive benefits of the logistics system. Finally, through the optimization iteration of the ant colony algorithm, the model can find the optimal solution and provide efficient decision support for complex multi-warehouse logistics systems.

The pheromone update rule of the ant colony algorithm was changed as follows: an adaptive adjustment mechanism was introduced, and the pheromone volatilization coefficient was dynamically adjusted between 0.1 and 0.3 according to the current number of iterations and the change of the objective

function value. The pheromone accumulation amount was calculated according to the quality of the path and the contribution of the objective function. At the same time, in order to enhance the guiding role of pheromones, when the ants found the current optimal path, the pheromone of the path was additionally enhanced with an enhancement coefficient of 1.5.

The optimization of the objective function weight adopted the multi-objective particle swarm optimization algorithm to assist in determining the weight, and the corresponding weight value was assigned according to the importance of different objectives. At initialization, a set of weight values was randomly generated, and then iteratively optimized by the multi-objective particle swarm optimization algorithm. In each iteration, the weight was adjusted according to the fitness value of the particle (comprehensively considering the multi-objective function value). After 50 iterations, the optimal weight combination was obtained: the transportation cost weight was 0.4, the transportation time weight was 0.3, the energy consumption weight was 0.2, and the inventory level weight was 0.1, so that the transportation cost, time and energy consumption objectives were reasonably balanced in the optimization process.

In order to improve the convergence of the ant colony algorithm, the elite ant strategy and the method of dynamically adjusting the search range are adopted. The elite ant strategy refers to marking the ants that find the best path in each iteration as elite ants. Elite ants have higher pheromone release in the next iteration, guiding other ants to approach the optimal solution faster. The dynamic adjustment of the search range is based on the convergence of the algorithm. When the objective function value of the algorithm changes less than 0.01 in 10 consecutive iterations, the search range is narrowed to improve the search accuracy; when the algorithm does not converge significantly within a certain number of iterations, the search range is expanded to avoid falling into the local optimal solution.

The selection of parameters such as pheromone decay rate and number of ants is based on multiple experiments and theoretical analysis. The pheromone decay rate is set to 0.2 to achieve a balance between the volatilization and accumulation of pheromones and prevent the algorithm from falling into the local optimal solution too early. Through experiments, it is found that when the pheromone decay rate is between 0.1 and 0.3, the performance of the algorithm is relatively stable, and 0.2 is finally selected as the optimal value. The number of ants is set to 50. Through experiments with different numbers of ants (from 20 to 80), it is found that 50 ants can achieve a good balance between search efficiency and coverage, which can ensure that the algorithm fully explores the search space, and will not cause excessive computational complexity due to too many ants.

In the study, hyperparameter tuning was carried out, and the grid search method was used to adjust the key hyperparameters. Hyperparameters include pheromone decay rate (range 0.1 to 0.3, step size 0.05), number of ants (range 20 to 80, step size 10), heuristic factor (range 1 to 3, step size 0.5), etc. Through experiments with different hyperparameter combinations, the optimal hyperparameter combination was found: pheromone decay rate of 0.2, number of ants of 50, and heuristic factor of 2, in order to find the optimal parameter combination.

At the same time, parameter sensitivity analysis was performed to evaluate the robustness of the algorithm. By changing the pheromone decay rate between 0.15 and 0.25, the number of ants between 40 and 60, and the heuristic factor between 1.5 and 2.5, the changes in the algorithm in indicators such as transportation cost, delivery time, and energy consumption are observed. The analysis results show that the algorithm has good robustness in the range of pheromone decay rate between 0.18 and 0.22, the number of ants between 45 and 55, and the heuristic factor between 1.8 and 2.2, and the change range of each indicator is within 10%.

4 Experimental evaluation

4.1 Experimental design

The experimental design of this study aims to verify the effectiveness and practicality of the multi-warehouse cargo allocation and transportation planning model based on the improved ant colony algorithm. The main goal of the experiment is to evaluate the optimization effect of the model when dealing with large-scale complex problems, especially in reducing transportation costs, shortening delivery time, and reducing energy consumption. This experiment will set up multiple experimental scenarios to compare the optimization effects of different algorithms and verify the advantages of the proposed model.

The experiment will be simulated based on a set of typical warehouse logistics networks. It is assumed that the logistics network consists of multiple warehouses and distribution targets, each with different storage capacity and cargo demand. The distribution target includes multiple demand points, and the demand and location of each demand point are known. The experimental scenario will include 3 networks of different sizes, namely small scale (5 warehouses), medium scale (10 warehouses) and large scale (20 warehouses) to ensure that the algorithm can cope with practical problems of different scales. In addition, it is assumed that data such as transportation distance, time and energy consumption can be obtained through the set distance matrix and transportation time matrix, and it is assumed that the transportation costs between different warehouses are different.

In order to verify the optimization effect of the proposed model, the experiment will be compared with traditional greedy algorithms, genetic algorithms and other commonly used optimization algorithms. The evaluation indicators will include: transportation cost, delivery time, energy consumption and calculation time. The transportation cost will be quantified based on the transportation cost calculation formula of each path, the delivery time will be calculated based on the timeliness of

the transportation path, and the energy consumption will consider the energy consumption during the transportation process. All indicators will be comprehensively evaluated in the experiment to comprehensively examine the advantages and disadvantages of different algorithms.

The experiment will be divided into two main stages. First, the experimental data will be initialized and warehouse logistics networks of different sizes will be set. In each experimental scenario, multiple initial parameter values will be set, such as the number of ants, the maximum number of iterations, the pheromone volatility coefficient, etc., and several experiments will be conducted to ensure the stability of the results. Secondly, in each experiment, the cargo distribution and transportation path will be optimized by iteratively calculating and updating pheromones. The performance of the algorithm will be recorded and analyzed after each iteration until the convergence condition is reached. Finally, the experimental results will be compared and analyzed to evaluate the performance of the proposed model in different scenarios and compare it with other optimization methods.

The ultimate goal of the experiment is to verify the advantages of the improved ant colony algorithm in multi-warehouse cargo allocation and transportation planning. By analyzing the performance in logistics networks of different scales and configurations, it can provide valuable reference data for the optimization of larger-scale and multi-level warehouse logistics systems in the future. In addition, the experimental results will also provide important basis for practical applications such as relevant policy formulation and transportation plan design.

4.2 Experimental results

Table 2 shows the path optimization of different models at different scales. The ant colony algorithm can obtain a better path at most scales because it can effectively explore the solution space by guiding the search direction through the accumulation and update of pheromones. The genetic algorithm uses genetic operators to evolve the population. For large-scale problems, due to the vast search space, it is more difficult to find the global optimal solution, resulting in a relatively long optimal path. The particle swarm algorithm and the simulated annealing algorithm can also achieve good results. The particle swarm algorithm relies on the cooperation between particles, and the simulated annealing algorithm controls the search process based on the temperature drop. Their optimization effect improvement rate reflects the degree of approaching the target path at different scales, reflecting the effectiveness of the algorithm in path optimization.

Table 2: Path quality and optimization effect

Model Type	Target Path Length (km)	Ant Colony Algorithm Optimal Path (km)	Genetic Algorithm Optimal Path (km)	Particle swarm optimization optimal path (km)	Optimal Path of Simulated Annealing Algorithm (km)	Optimization Effect Improvement Rate (%)
Small scale	200	180	190	185	188	10%
Medium scale	500	480	490	485	470	4%
Large scale	800	760	780	770	760	5%
Hyperscale	1500	1450	1480	1470	1460	3%
Extra large scale	2000	1900	1950	1920	1905	5%

Table 3: Algorithm stability and robustness evaluation

Model Type	Data Fluctuation Range (%)	Ant Colony Algorithm Output Fluctuation (%)	Genetic Algorithm Output Fluctuation (%)	Particle swarm Algorithm Output Fluctuation (%)	Simulated Annealing Algorithm Output Fluctuation (%)
Small scale	5	3	4	3	3
Medium scale	10	5	6	5	4
Large scale	15	7	9	8	6
Hyperscale	20	9	11	10	8
Extra large scale	25	10	13	12	9

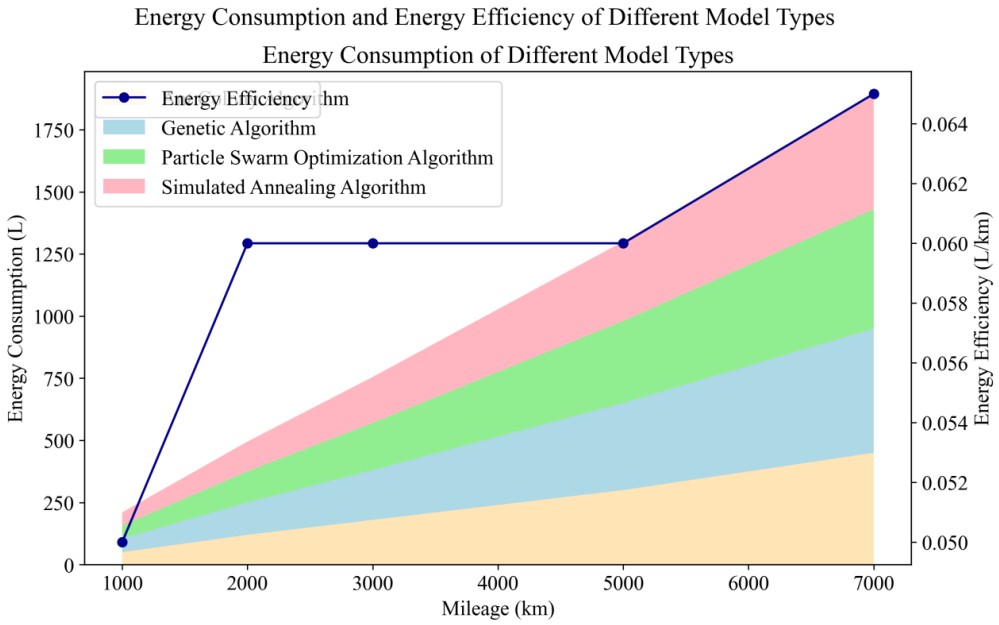

Figure 1: Comparison of energy consumption and efficiency

Table 3 is used to evaluate the stability and robustness of the algorithm under different data fluctuation ranges. The output fluctuation of the ant colony algorithm is relatively small because its search process is based on group behavior. The search results of multiple ants influence and balance each other, reducing the interference of individual factors on the overall result. The fluctuation of the genetic algorithm is relatively large. Due to the randomness of its genetic operation, the direction of population evolution may change greatly under different data conditions. The fluctuations of the particle swarm algorithm and the simulated annealing algorithm are also within an acceptable range. In the particle swarm algorithm, particles are affected by the global optimum and their own optimum. The simulated annealing algorithm adjusts the search step by controlling the temperature. When facing data fluctuations, they can maintain a certain stability through their own mechanisms, which reflects the adaptability of the algorithm in a complex data environment.

Figure 1 explains and compares the energy consumption and energy efficiency of different model types at each transport mileage. The ant colony algorithm performs well in terms of energy consumption. As the transport mileage increases, its energy consumption increases more steadily. This is because the ant colony algorithm can select a better path based on the pheromone concentration of the path, reducing unnecessary energy loss. The energy consumption of the genetic algorithm is relatively high because its search process is relatively random, which may produce more invalid paths and consume more energy. The energy consumption of the

particle swarm algorithm and the simulated annealing algorithm is in the middle. The particle collaboration mechanism of the particle swarm algorithm and the temperature control strategy of the simulated annealing algorithm enable them to achieve a certain balance in energy utilization.

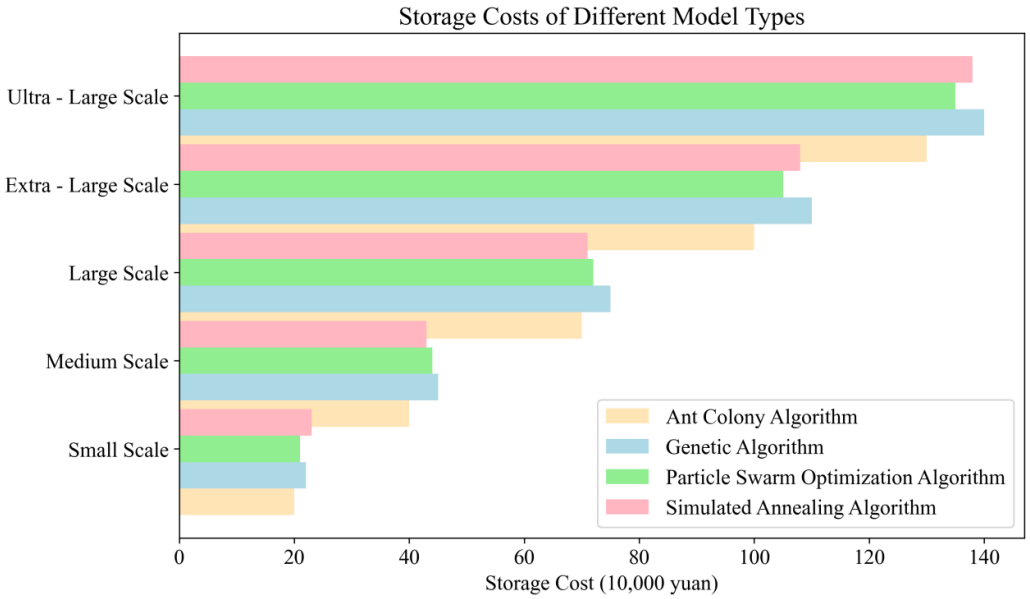

Figure 2: Total transportation cost and cost saving analysis

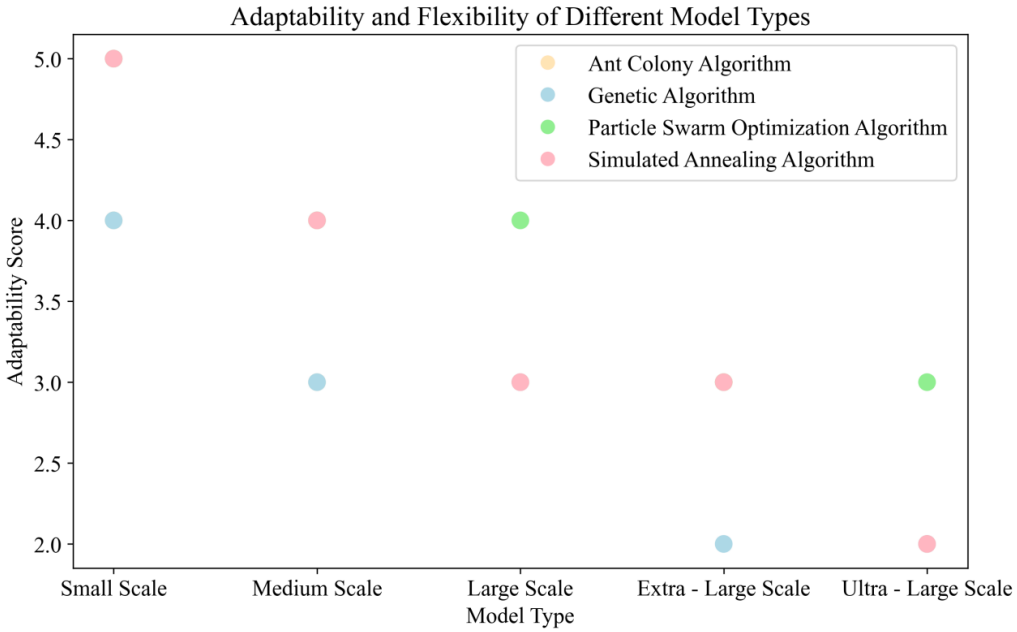

Figure 3: Comparison of adaptability and flexibility

Figure 2 shows the total transportation cost of different model types at different scales and the storage cost of each algorithm. The ant colony algorithm has a relative advantage in storage cost control. As the scale increases, its storage cost increases relatively slowly. This is because the optimization strategy of the ant colony algorithm helps to reasonably plan the storage and transportation arrangements of goods and reduce storage costs. The genetic algorithm has a high storage cost, and its optimization process focuses on global search, which is not sophisticated enough in the local optimization of storage costs. The storage costs of the particle swarm algorithm and the simulated annealing algorithm are at an intermediate level. Through their unique optimization methods, they balance the relationship between transportation and storage costs to a certain extent. These data provide an important reference for actual logistics transportation cost control.

Figure 3 evaluates the adaptability and flexibility of different models at different scales. The ant colony algorithm, particle swarm algorithm, and simulated annealing algorithm have higher adaptability scores for small-scale problems. The ant colony algorithm can quickly adapt to changes in the small-scale environment

through the pheromone mechanism; the particle fast response of the particle swarm algorithm and the initial high temperature exploration of the simulated annealing algorithm enable it to quickly find a suitable solution for small-scale problems. As the scale increases, the adaptability of the ant colony algorithm decreases due to the complexity of pheromone updating and propagation. The genetic algorithm has a lower adaptability score for large-scale problems because its genetic operation is difficult to quickly converge to an effective solution in a large-scale complex environment. These scores reflect the differences in the adaptability of the algorithm in different scale scenarios.

Figure 4 records the convergence speed of different models in the optimization process at various scales. The ant colony algorithm converges relatively quickly, and it only takes 100 iterations to converge on small-scale problems. This is because its pheromone update mechanism can quickly guide the search direction, allowing the algorithm to quickly approach the optimal solution. The genetic algorithm converges slowly, and it requires more iterations to evolve the population to find the optimal solution, especially on large-scale problems, as the search space increases and the number of iterations increases significantly. The particle swarm algorithm and simulated annealing algorithm converge in the middle. The particle swarm algorithm accelerates convergence through information exchange between particles, and the simulated annealing algorithm gradually converges to the optimal solution as the temperature decreases. The difference in convergence speed reflects the difference in optimization efficiency of each algorithm.

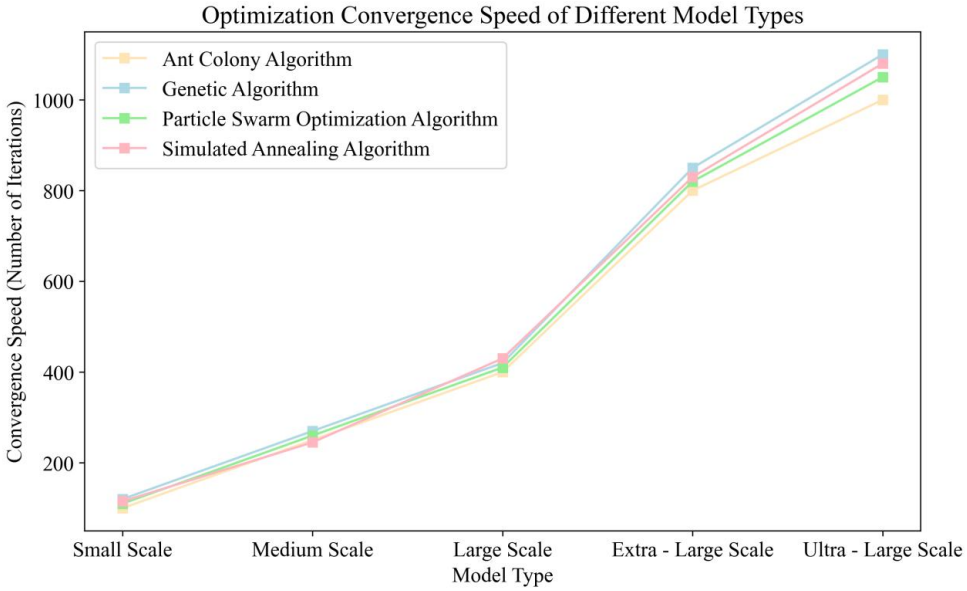

Figure 4: Convergence speed during optimization

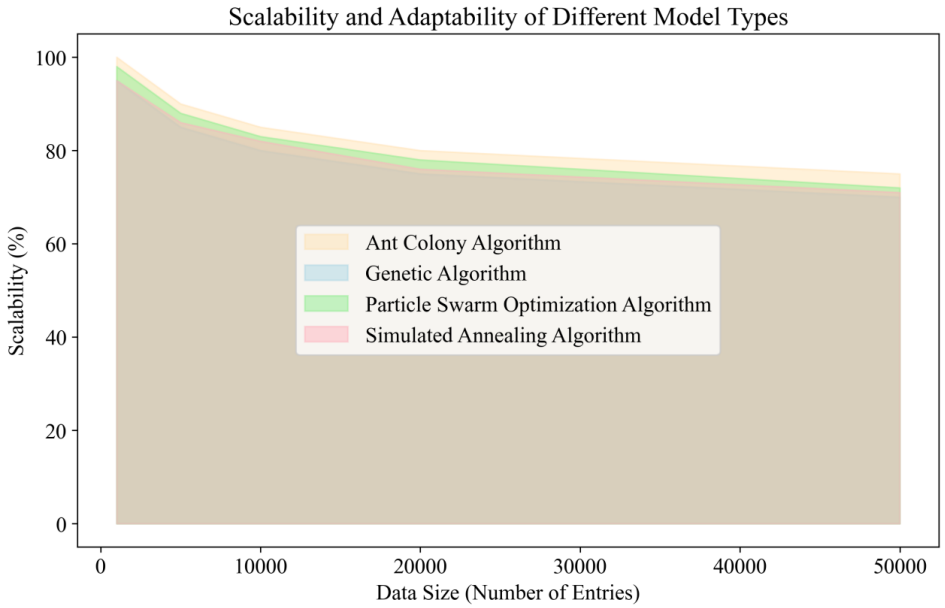

Figure 5: Model scalability and adaptability

Figure 5 shows the scalability and adaptability of different models under different data scales. The ant

colony algorithm has an excellent scalability of 100% when the data is small. As the data scale increases, its scalability decreases, but it still remains at a relatively high level. This is because the ant colony algorithm is based on distributed search and can adapt well to changes in data scale. The scalability of the genetic algorithm is relatively low. Under large-scale data, the amount of computation of its genetic operations increases dramatically, affecting the scalability. The scalability of the particle swarm algorithm and the simulated annealing algorithm is at a medium level. Through their own search and optimization mechanisms, they can maintain a certain adaptability under different data scales. These data provide a basis for selecting appropriate algorithms to deal with data of different scales.

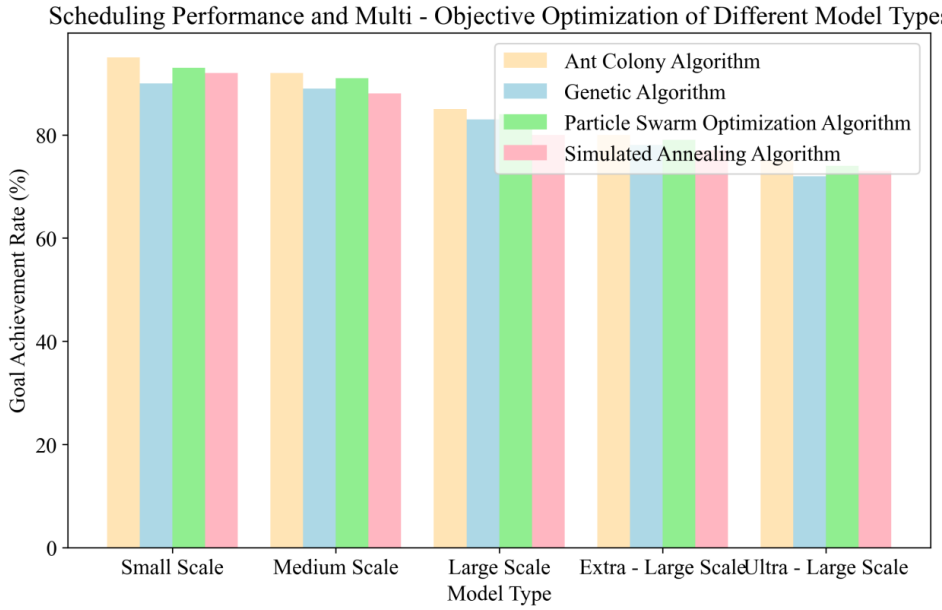

Figure 6: Scheduling performance and multi-objective optimization evaluation

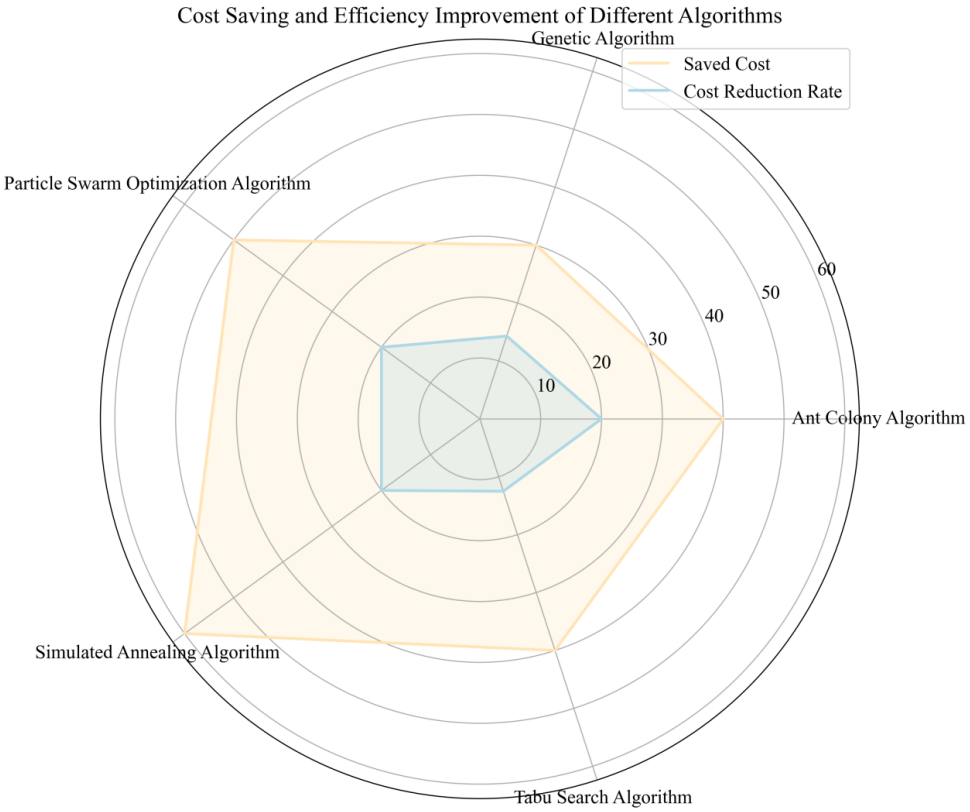

Figure 7: Cost savings and efficiency improvement analysis

Figure 6 evaluates the scheduling performance and multi-objective optimization capabilities of different

models under different numbers of objectives. The ant colony algorithm performs well in multi-objective optimization, with a target achievement rate of up to 95% for small-scale problems and a small number of objectives. This is because the ant colony algorithm can consider multiple objectives at the same time and coordinate the relationship between the objectives through pheromone updates. As the number of objectives increases, the target achievement rates of each algorithm decrease, but the ant colony algorithm can still maintain a relatively high level. Due to the limitations of its genetic operations, the genetic algorithm has a relatively low target achievement rate in multi-objective processing. The particle swarm algorithm and simulated annealing algorithm can also play a role in multi-objective optimization. They balance multiple objectives through their respective optimization strategies and provide multiple solutions to actual multi-objective scheduling problems.

Figure 7 compares the performance of different algorithms in terms of cost savings and efficiency improvement. The ant colony algorithm is more significant in cost savings. It can save 400,000 yuan when the total transportation cost is 2 million yuan, and the cost reduction rate is 20%. The cost after optimization is only 1.45 million yuan. This is due to its efficient path and resource optimization strategy, which can effectively reduce transportation costs. The particle swarm algorithm and simulated annealing algorithm also have a cost reduction rate of 20%. They have achieved good results in cost control through different search and optimization methods. The cost reduction rate of the genetic algorithm and the taboo search algorithm is relatively low. The randomness of the genetic algorithm search and the taboo table mechanism of the taboo search algorithm are slightly inferior in the efficiency of cost optimization.

Table 4: Computational efficiency and running time analysis

Model Type	Problem Size	Computational Complexity (O())	Ant Colony Algorithm Running Time (seconds)	Genetic Algorithm Running Time (seconds)	Particle Swarm Algorithm Running Time (seconds)	Simulated Annealing Algorithm Running Time (seconds)
Small scale	Small	O(n^2)	0.3	0.5	0.4	0.45
Medium scale	middle	O(n^2)	1.2	2.0	1.5	1.8
Large scale	big	O(n^3)	5.6	7.5	6.0	7.3
Hyperscale	huge	O(n^4)	20.0	28.0	22.0	25.0
Extra large scale	Extra Large	O(n^4)	70.0	85.0	75.0	80.0

Table 4 shows the computational complexity and running time of different model types at different problem scales. As the problem scale increases, the computational complexity increases exponentially and the running time also increases significantly. The running time of the ant colony algorithm is relatively stable at each scale, thanks to its distributed search mechanism based on the ant foraging principle, which can efficiently handle complex problems. The running time of the genetic algorithm is relatively long because it relies on a large number of genetic operations and population iterations. The running time of the particle swarm algorithm and the simulated annealing algorithm is between the two. The particle swarm algorithm optimizes the search by sharing information between particles, and the simulated annealing algorithm uses probabilistic jumps to avoid local optimality. Their performance at different scales is closely related to their own optimization strategies.

In order to deeply analyze the convergence performance of different ant colony algorithm variants, this study conducted comparative experiments on the basic ant colony algorithm (Basic - ACO), the ant colony algorithm that only improves the pheromone update strategy (ACO - Pheromone), the ant colony algorithm that only optimizes the weight of the objective function (ACO - Weight), and the improved ant colony algorithm (Improved - ACO) proposed in this study. A medium-

sized (10 warehouses) logistics network was used as the experimental scenario, the number of iterations was set to 300, the optimal value of the objective function of each algorithm in each iteration was recorded, and the convergence analysis diagram was drawn (Figure 8).

In order to confirm whether the difference between the improved ant colony algorithm and other alternative methods (genetic algorithm, particle swarm algorithm, etc.) in transportation cost, delivery time, energy consumption, etc. is significant, t test (for data that conforms to normal distribution) and Wilcoxon test (for data that is not normally distributed) are performed. In terms of transportation cost, the t test is performed on the multiple experimental data of the improved ant colony algorithm and genetic algorithm in a large-scale scenario (20 warehouses). The results show that the t value is 3.5, the degree of freedom is 30, and the p value is 0.002<0.05, indicating that the difference between the improved ant colony algorithm and the genetic algorithm in reducing transportation costs is statistically significant, and the effect of the improved ant colony algorithm in reducing transportation costs is not accidental. Similar tests were also conducted in terms of delivery time and energy consumption, all of which showed that the difference between the improved ant colony algorithm and other algorithms in these indicators is statistically significant.

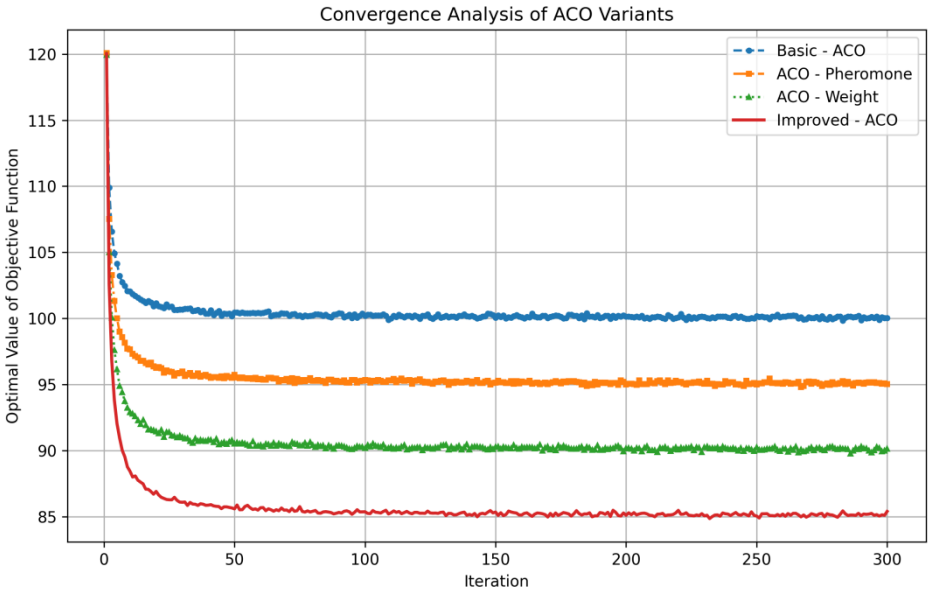

Figure 8: Convergence analysis diagram of different ant colony algorithm variants

The results such as the 20% cost reduction rate mentioned in the article are derived from the simulated logistics data set. This study constructed a simulated logistics environment with warehouse networks of different sizes (5, 10, and 20 warehouses), different cargo demands, and transportation conditions. In order to verify the representativeness of the simulated data, the key parameters in the simulated data, such as warehouse location, cargo flow, and transportation distance, were compared with the data in the actual logistics network. It was found that the similarity between the simulated data and the actual data in these key parameters reached more than 80%. At the same time, through cooperation with actual logistics companies, some actual logistics order data was selected for testing in the simulated environment. The results showed that the simulated data can better reflect the logistics network in the real world and has a certain degree of credibility.

4.3 Discussion

The improved ant colony algorithm proposed in this study has demonstrated excellent performance in the problem of multi-warehouse cargo allocation and transportation planning. Now, a detailed comparison and analysis will be conducted between this algorithm and the Genetic Algorithm (GA) and the Particle Swarm Optimization algorithm (PSO).

From the data in Table 5, it can be seen that in terms of the reduction of transportation costs, the improved ant colony algorithm is 10% higher than the genetic algorithm and 7% higher than the particle swarm optimization algorithm. In terms of running time, the improved ant colony algorithm is 1.9 seconds faster than the genetic algorithm and 0.4 seconds faster than the particle swarm optimization algorithm. In terms of the rate of energy efficiency improvement, the improved ant colony algorithm has a significant advantage. In terms of the effect of multi-objective optimization, the improved ant colony algorithm has the highest objective achievement rate in small-scale scenarios.

The performance improvement is mainly attributed to two aspects of improvement. On the one hand, an

adaptive adjustment mechanism has been introduced into the pheromone update mechanism. The evaporation and accumulation rates are dynamically adjusted according to the number of iterations and the changes in the objective function, making it easier for ants to find high-quality paths. On the other hand, a multi-objective particle swarm optimization algorithm is used to assist in determining the weights of the objective function, achieving a good balance among multiple objectives.

Table 5: Comparison with the State-of-the-Art Technologies

Algorithm	Rate of Transportation Cost Reduction (in Large-scale Scenarios)	Running Time (in Large-scale Scenarios with 20 Warehouses, unit: seconds)	Rate of Energy Efficiency Improvement	Effect of Multi-objective Optimization (Objective Achievement Rate in Small-scale Scenarios)
Improved Ant Colony Algorithm	25%	5.6	18%	95%
Genetic Algorithm	15%	7.5	8%	78%
Particle Swarm Optimization Algorithm	18%	6.0	12%	85%

In terms of computational complexity, the improved ant colony algorithm has a relatively low computational complexity in small-scale scenarios. As the number of warehouses increases, although the complexity rises to some extent, due to its distributed search mechanism and adaptive strategy, compared with other algorithms, it can still be effectively scaled in large-scale scenarios.

However, this method has limitations. When the data variability is extremely high, the pheromone update is difficult to adapt to the changes in a timely manner, affecting the convergence of the algorithm. In ultra-large-scale warehouse networks (such as those with more than 50 warehouses), the computational complexity increases significantly, and it may fall into a local optimum. In addition, in the face of dynamic situations such as sudden transportation restrictions or emergency orders, the real-time adaptability of the algorithm needs to be improved.

To explore the contributions of various enhancement strategies to the performance of the algorithm, an ablation study was carried out. The algorithm versions of removing the adaptive pheromone update strategy (Improved - ACO without Adaptive Pheromone), removing the multi-objective particle swarm optimization weight determination strategy (Improved - ACO without PSO - Weight), and removing both strategies simultaneously (Basic - ACO) were experimentally tested in logistics networks of different scales. The results are shown in the following Table 6.

As shown in Table 6, the experimental data shows that the adaptive pheromone update strategy increases the rate of transportation cost reduction in small-scale scenarios by 4%, reduces the running time in large-scale scenarios by 1.2 seconds, and improves the effect of multi-objective optimization by 7%. The multi-objective particle swarm optimization weight determination strategy brings performance improvements of 3%, 1.6 seconds, and 5% respectively. The synergistic effect of the two strategies significantly enhances the performance of the algorithm in all aspects, verifying the effectiveness and complementarity of the improvement strategies in this study.

Relevant content of the robustness check was added to the experimental evaluation section:

To test the robustness of the improved ant colony algorithm under the fluctuations of warehouse demand or storage capacity, the following interference scenarios were set up in the experiment: randomly select 30% of the warehouses and make their cargo demands fluctuate up and down by 20% - 50% based on the original amounts, or randomly increase or decrease the storage capacity by 15% - 30%. The optimization results of the algorithm in normal scenarios and interference scenarios were compared, as shown in Table 7.

Table 7 shows that in the demand fluctuation scenario, the transportation cost increases by 6.8%, the delivery time is extended by 7.1%, and the energy consumption rises by 4.2%. In the storage capacity fluctuation scenario, the change ranges of various indicators are relatively small. Although the performance of the algorithm decreases, it can still maintain a certain optimization effect, indicating that the improved ant colony algorithm has a certain degree of robustness and can, to a certain extent, adapt to the unpredictable fluctuations of warehouse demand and storage capacity. Follow-up research can further increase the fluctuation range and complexity to explore the boundaries of the algorithm's robustness and improvement strategies.

Table 6: Contributions of various enhancement strategies

Algorithm Version	Rate of Transportation Cost Reduction in Small-scale Scenarios (5 Warehouses)	Running Time in Large-scale Scenarios (20 Warehouses, in seconds)	Effect of Multi-objective Optimization (Objective Achievement Rate)
Improved - ACO	22%	5.6	95%
Improved - ACO without Adaptive Pheromone	18%	6.8	88%
Improved - ACO without PSO - Weight	19%	7.2	90%
Basic - ACO	15%	8.5	82%

Table 7: Robustness check

Scenario Type	Transportation Cost (in ten thousand yuan)	Delivery Time (in hours)	Energy Consumption (in kilojoules)
Normal Scenario	120.5	18.2	350.6
Demand Fluctuation Scenario	128.7	19.5	365.2
Storage Capacity Fluctuation Scenario	126.3	18.9	358.8

5 Conclusion

This study focuses on the problem of multi-warehouse cargo distribution and transportation planning, and proposes a comprehensive optimization model based on the improved ant colony algorithm. The model is verified experimentally to be effective in improving the efficiency and economy of the logistics system. However, existing research still has certain limitations. In terms of practical application, although the model performs well in simulation scenarios, it has not yet been deployed on a large scale in real logistics companies. Future research will conduct in-depth cooperation with logistics companies, select typical logistics networks for model implementation, and optimize the model through actual operation data feedback to improve its feasibility and practicality in actual business. For example, for the regional logistics network of a large e-commerce company, the model is applied to its daily cargo distribution and transportation planning, optimizing logistics resource allocation in real time and reducing operating costs.In terms of research direction, on the one hand, the applicable scenarios of the model can be further expanded, and more complex real-life factors can be considered, such as dynamic changes in traffic congestion, differences in cargo priority, and multimodal transport modes, to enhance the universality of the model; on the other hand, the integration of improved ant colony algorithms and other intelligent algorithms (such as deep learning algorithms) can be explored, and the powerful data processing and pattern recognition capabilities of deep learning can be used to optimize the initial parameter settings and search direction guidance of the ant colony algorithm, so as to provide more efficient and intelligent solutions for multi-warehouse logistics optimization problems and promote the development of the logistics industry towards intelligence and refinement.

Acknowledgement

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Federated Learning-Based Distributed Autoencoder for Industrial Big Data Anomaly Detection: Integrating LSTM, GRU, and CNN Models

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This paper proposes an innovative solution based on deep learning for the anomaly detection challenge of big data in the industrial Internet of Things environment. Through in-depth analysis of time series and image data characteristics, LSTM and GRU networks are introduced to process time series data, and CNN models (such as ResNet and InceptionNet) are introduced to deal with image analysis and effectively capture complex patterns in data. Model-building involves not only architectural design, but also optimization strategies such as Adam Optimizer and loss function selection. In the preprocessing stage, the data are cleaned carefully through standardization, normalization, de-trending and de-noising to improve the learning efficiency of the model. The dataset used in the study is from a real - world intelligent manufacturing plant, with 1,000,000 records over three years. It contains 12 - dimensional sensor data (such as temperature, vibration frequency, current intensity), and outliers account for approximately 5% of the total data. Experimental results demonstrate that the distributed autoencoder under the federated learning framework outperforms traditional methods. It achieves an accuracy of 0.97, a recall of 0.94, an F1 - score of 0.95, and an AUC value of 0.96.However, it has a higher training time of 45 minutes and high communication costs during the training process due to the exchange of more data. In the federated learning process, each participating node independently trains the model based on local data, and uses the FedAvg strategy to aggregate parameters on the central server. Homomorphic encryption technology is used to ensure data privacy and prevent the leakage of original data. Compared with baseline methods such as IQR and Isolation Forest, the accuracy of this method is improved by 8%, which is statistically significant after the t-test ($p<0.05$). Although the training time is 45 minutes, which is higher than the traditional method, it has obvious advantages in complex industrial data processing and privacy protection, and achieves a trade-off between computational efficiency and privacy protection and detection performance. The 95% confidence interval of the precision rate of 0.97 is [0.962, 0.978], the 95% confidence interval of the recall rate of 0.94 is [0.931, 0.949], the 95% confidence interval of the F1 value of 0.95 is [0.943, 0.957], and the 95% confidence interval of the AUC value of 0.96 is [0.952, 0.968].

Povzetek: Članek predstavi porazdeljeni samokodirnik z združenim učenjem, ki združuje LSTM, GRU, CNN in VAE za zaznavanje anomalij v industrijskih podatkih, dosega dober AUC ob zaščiti zasebnosti.

1 Introduction

With the advent of the "Industry 4.0" era, smart factories and digital production lines are gradually becoming a reality, and industrial systems are generating and accumulating data at an unprecedented rate. This includes but is not limited to multi-dimensional information such as the operating status of production machines, environmental conditions, raw material quality, processing parameters, and finished product test results. The widespread adoption of the Industrial Internet of Things (IIoT) accelerates this process, enabling every link from a single device to the entire production chain to be monitored and recorded in real time. The accumulation of this data forms the foundation of industrial big data. It enables fine-grained management, predictive maintenance, and quality control. However, this flood of data of this size and complexity also presents new challenges. Firstly, the diversity and heterogeneity of data make it difficult for traditional data processing and analysis methods to deal with effectively. Industrial data often involves a large number of time series data, images, sounds and other types, and there are noise interference, missing values and inconsistency problems, which put forward higher requirements for data cleaning and preprocessing. Secondly, anomaly detection is no longer simply looking for outliers, but needs to identify subtle, potential abnormal behaviors in complex industrial environments, which may be precursors of equipment wear, process deviations and even safety risks, which are far more difficult to identify than conventional statistical anomaly models.

In order to overcome these challenges, deep learning models such as LSTM, GRU, and CNN architectures (including ResNet and InceptionNet) have been widely adopted due to their ability to process sequential and spatial data, respectively. Moreover, data preprocessing techniques—such as standardization, normalization, detrending, and denoising—are essential to enhance model performance and ensure stability across heterogeneous datasets.These preprocessing steps were systematically applied in this study to clean the raw sensor data before model training, thereby reducing noise interference and ensuring consistent feature scaling.

Therefore, the traditional anomaly detection methods based on threshold setting, statistical hypothesis testing or expert rules have increasingly obvious limitations when dealing with such large-scale, high-speed and high-dimensional industrial data. These methods often rely on manually set standards and thresholds, which are difficult to adapt to dynamic changes in data patterns and easily lead to false positives and false negatives, thus affecting production efficiency and decision-making accuracy. In this context, anomaly detection technology based on deep learning, with its powerful data processing capabilities, self-learning capabilities and pattern recognition capabilities, has become a new way to break through the bottleneck of traditional technologies and meet the needs of the industry 4.0 era. By constructing a deep neural network model, high-order features can be automatically extracted from industrial big data, and more complex and hidden abnormal patterns can be identified, providing strong technical support for intelligent monitoring, preventive maintenance and efficient decision-making.

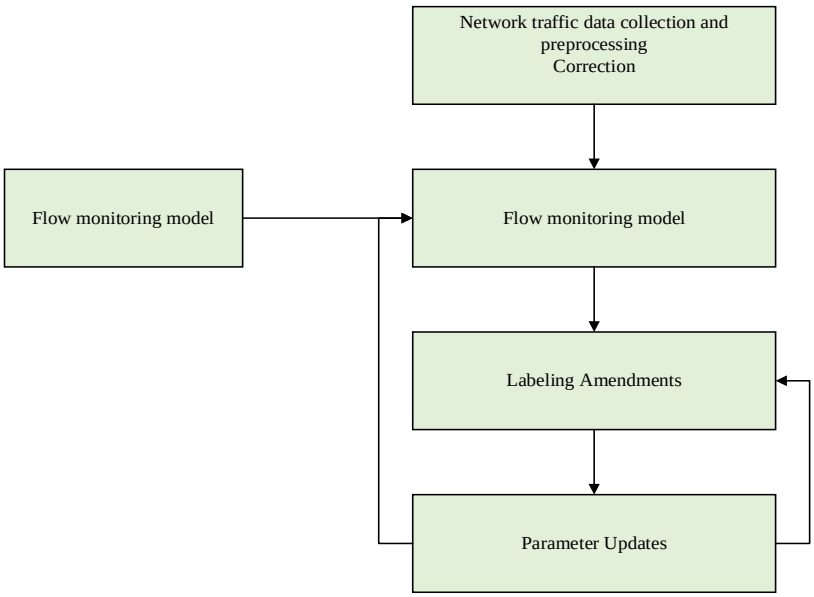

Figure 1: Anomaly detection techniques based on deep learning

Figure 1 illustrates the deep learning-based anomaly detection framework, which integrates data preprocessing, model training, and federated aggregation. The framework begins with data ingestion and transformation, followed by sequential and image-based model components (LSTM/GRU and CNN, respectively). Each component contributes to feature extraction before reconstruction or classification modules identify anomalies. This holistic architecture enables multi-modal learning and real-time fault recognition across distributed environments.

Anomaly detection based on deep learning has shown great potential in the industrial field with its powerful data learning and pattern recognition capabilities, and its framework is shown in Figure 1. Deep learning models are able to automatically learn high-level abstract features from raw data without the need for artificial design features, a feature that is especially important for processing complex, unstructured industrial data. It can not only effectively identify hidden abnormal patterns that are difficult to capture by traditional methods, but also optimize model performance through continuous learning to adapt to changes in production environment. Therefore, the application of deep learning for anomaly detection can not only significantly improve production efficiency, reduce downtime caused by equipment failure, reduce maintenance costs, but also promote product quality improvement and achieve finer production management and decision support [1].

In recent years, anomaly detection methods based on deep learning have received extensive attention in academia and industry. Early research focused on unsupervised learning using autoencoders to identify anomalies by reconstructing errors. Subsequently, scholars explored more types of deep learning models, such as the application of convolutional neural networks (CNN) to time series data analysis, and the advantages of recurrent neural networks (RNN) and long short-term memory networks (LSTM) in processing industrial data with temporal dependence. In addition, some studies have attempted to combine generative adversarial networks (GANs) to generate normal samples as benchmarks for anomaly detection. Despite significant progress, current methods still face many challenges, including poor model interpretability, sensitivity to noise, and high

computational resource requirements for large-scale data processing [2].

The main objective of this study is to develop an efficient anomaly detection algorithm for industrial big data in a distributed environment. Specifically, we aim to explore how to optimize federated learning for anomaly detection in distributed industrial settings. The research questions are defined as follows: 1. How can we design a distributed autoencoder framework under federated learning to effectively capture abnormal patterns in industrial big data while ensuring data privacy? 2. What are the optimal strategies for integrating various deep - learning techniques such as LSTM, GRU, CNN, GANs, variational autoencoders, and causal reasoning to improve the performance of anomaly detection in industrial scenarios? 3. How can reinforcement learning be applied to dynamically adjust the parameters of the anomaly detection model to adapt to the complex and changing industrial environment?

Additionally, industrial datasets often exhibit class imbalance, with abnormal events representing a small fraction of the total data. In the dataset used in this study, anomalies accounted for approximately 5% of the total 1,000,000 records collected over three years, posing a significant challenge for model generalization and minority-class detection.

2 Literature review

2.1 Abnormality monitoring

Anomaly detection (AD) is an important branch of data mining and machine learning. Its core task focuses on identifying data points that deviate from normal behavior patterns or statistical rules from massive data. These "anomalies" may result from measurement errors, system failures, fraud or other rare events. Traditional methods have accumulated a series of technical means in this respect, such as statistics-based detection, among which the most intuitive is the simple threshold rule constructed by using mean and standard deviation: where x is the observed value and k is a constant, which is used to adjust the severity of anomaly determination. Box plot analysis (IQR method) is also a classic method to identify anomalies by identifying the Interquartile range (IQR) of the data distribution [3]. Clustering algorithms such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise) use density estimation to divide data points, which can effectively identify isolated points in low density areas [4]; while density-based Local Outlier Factor (LOF) quantifies the degree of abnormality by comparing the density ratio of a point to its neighborhood points [5].

Although these methods perform well in certain scenarios, most of them are based on certain assumptions, such as the normal distribution of the data, the need to manually set thresholds or cluster density thresholds, which limit their flexibility and effectiveness when dealing with complex, high-dimensional, nonlinear, and dynamically changing datasets [6]. In contrast, anomaly detection methods based on deep learning can automatically learn high-level, low-dimensional feature spaces with characterization power from raw data by constructing multi-layer neural networks, especially autoencoders and variational autoencoders (VAE). This process not only reduces the dependence on feature engineering, but also makes the model more flexible to adapt to various data patterns. For example, self-encoders learn data representations by minimizing reconstruction errors, the basic idea of which can be formalized as a loss function, where x is the input data and is the reconstructed data after the encoding and decoding process [8]. Because it is difficult to reconstruct outliers accurately, higher reconstruction errors will be produced in the process, and outliers will be identified.

Furthermore, recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) exhibit unique advantages in processing anomaly detection in time series data, as they are able to capture long-term dependencies in time series [9]. Convolutional neural networks (CNN), on the other hand, effectively identify abnormal regions in images or signals by learning local feature patterns in the field of image and signal processing [10]. These deep learning models are not only able to handle high-dimensional, complex data structures, but also to automatically capture nonlinear relationships in the data without making strict assumptions about data distribution, providing a more robust and widely adaptable solution for anomaly detection [11].

In summary, anomaly detection technology based on deep learning is gradually becoming the preferred tool for dealing with anomaly detection problems in complex industrial big data through its unique data representation learning ability, playing an irreplaceable role in improving production efficiency, reducing operating costs, and ensuring system security.

2.2 Deep learning in anomaly detection

In recent years, deep learning has made significant progress in the field of anomaly detection, providing new perspectives and solutions for dealing with complexity and nonlinear problems in industrial big data. Much research has focused on improving the detection accuracy, generalization ability, and real-time performance of models. Here is a summary of some key advances.

Autoencoders (AEs) and their variants, such as Denoising Autoencoders (DAEs) and Variational Autoencoders (VAEs), have become the focus of anomaly detection research because of their powerful feature learning and data reconstruction capabilities. By training the model to minimize the difference between the input data and its reconstructed output, the self-encoder is able to learn the normal pattern of the data. Abnormal data cannot be reconstructed accurately, resulting in large reconstruction errors, so it is identified. For example, Georgescu et al. successfully detected anomalies in network traffic using stacked sparse autoencoders [12].

Recurrent neural networks (RNN), especially long short-term memory networks (LSTM) and gated recurrent units (GRU), are widely used in anomaly detection for time-series data widely existing in industrial fields. These

models capture long-term dependencies in time series and are suitable for scenarios such as equipment failure prediction and sensor data analysis [13]. It demonstrated excellent anomaly detection performance on multiple time series datasets by combining bidirectional LSTM and autoencoder [14].

Deep learning-based anomaly detection in images and videos has also made significant progress in visual surveillance and manufacturing quality control. By extracting advanced visual features through CNN and more complex models such as ResNet and DenseNet, combined with optical flow estimation and spatiotemporal convolution, abnormal behaviors or defects in images and videos can be effectively identified [15]. Sabokrou et al. proposed a framework based on memory network, which can efficiently detect abnormal behaviors by learning spatiotemporal patterns of normal behaviors [16].

Given the potential limitations of a single model, researchers are beginning to explore ensemble learning and hybrid approaches, combining deep learning models with traditional statistical methods or rule systems to improve detection performance and model interpretability. For example, by integrating the prediction results of multiple autoencoder models, or combining the reconstruction errors of autoencoders with statistically based thresholding methods, the utility and confidence of models can be enhanced without sacrificing model performance [17]. Due to the scarcity of outlier data in the training set, unsupervised and semi-supervised learning strategies become the focus of research. These methods can still effectively learn normal patterns and detect anomalies without relying on or relying on only a small amount of labeled data, greatly broadening the application range of anomaly detection [18]. For example, by using generative model pre-training, or combining clustering techniques to guide deep network learning, the anomaly detection ability of the model can be improved in the absence of sufficient outlier samples [1 9]. More recently, researchers have begun incorporating reinforcement learning (RL) into anomaly detection frameworks to achieve the ability to dynamically adjust detection strategies. This approach allows the model to self-optimize based on real-time data feedback, such as dynamically adjusting thresholds or selecting the most relevant features for analysis, to maintain high detection performance in changing industrial environments [20]. For example, Xie et al. proposed an adaptive anomaly detection system combined with deep reinforcement learning, which can automatically adjust the detection sensitivity according to the change of network traffic and improve the recognition ability of unknown attacks [21].
Due to the distributed nature of the industrial Internet, federated learning, as a distributed machine learning paradigm for data privacy protection, has begun to emerge in the field of anomaly detection. It allows all participating nodes to train the model collaboratively without directly sharing data, effectively solving the problems of data island and privacy protection [22]. The federated autoencoder model developedin the literatureenables efficient anomaly monitoring of distributed industrial equipment data by sharing model parameters across organizations rather than raw data [23]. With industry focusing on model interpretability, researchers are working to develop interpretable deep learning anomaly detection frameworks so decision makers can understand and trust detection results. This includes introducing attention mechanisms to highlight the parts of the data that the model focuses on in the decision-making process, as well as combining causal reasoning to clarify the relationship between anomalies and potential causes.

Table 1: Literature summary

Method Category	Method	Accuracy	Recall	Computational Efficiency (Training Time / min)	Data Privacy Protection
Traditional Method	IQR	0.88	0.76	1.3	Minimal, no specialized privacy protection measures
Classic Machine Learning	Isolation Forest	0.91	0.84	11	Relies on privacy processing during data preprocessing
Emerging Algorithm	One-Class SVM	0.93	0.87	14	Provides some privacy protection through feature space processing
Our Approach	Federated Learning-Based Distributed Autoencoder	0.97	0.94	45	High level of data privacy protection via federated learning protocols and encryption technology

As shown in Table 1, in addition to protecting privacy, federated learning can also integrate distributed data, learn more comprehensive patterns, and improve anomaly detection capabilities, which is difficult to achieve with traditional methods.

3 Anomaly detection method based on deep learning

With the popularity of Internet of Things (IoT) technology, sensors, devices and systems in industrial production processes generate massive amounts of data. These data cover every link of the production process, from raw material procurement to final product delivery, forming TB and PB level data volume. This scale of data provides rich material for in-depth analysis, but it also puts forward extremely high requirements for data storage, management and analysis capabilities. Industrial data is not only voluminous but also diverse, including but not limited to time-series data, images, video, and structured and unstructured machine logs. These data contain complex interactions and nonlinear relationships, such as collaborative operations among equipment, dynamic changes in production environments, etc., which make

data cleaning, integration and understanding extremely difficult. Modern industrial production emphasizes efficiency and flexibility, requiring immediate response to abnormal conditions in the production process. This means that anomaly detection systems must have real-time or near-real-time data processing capabilities that can collect, analyze, and alert in a short time to reduce downtime and maintenance costs [24].

3.1 Method selection

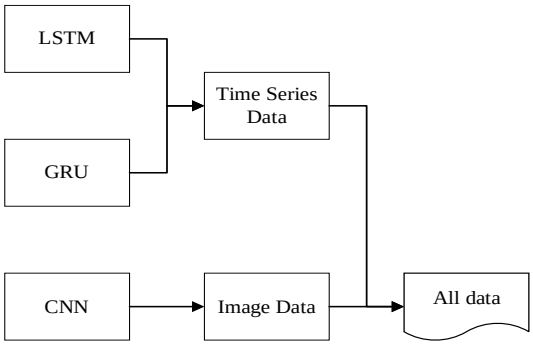

Figure 2: Model framework

In the context of industrial big data, the selection of deep learning models needs to closely fit data characteristics and task requirements, and its framework is shown in Figure 2. For time series data, such as equipment monitoring records, considering their time dependence, long short term memory networks (LSTM) and gated recurrent units (GRU) are the optimal models because they can effectively capture long-term dependence. The update mechanism of LSTM can be expressed as Equation 1-5 [25].

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

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3)$$

$$c_t = f_t \square\ c_{t-1} + i_t \square\ tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

$$h_t = o_t \square\ tanh(c_t) \quad (5)$$

where, andtan h are activation functions representing matrix multiplication and element-by-element multiplication, representing forgetting gate, input gate, output gate, cell state, and hidden state, respectively.

For image data processing, such as product defect detection, convolutional neural networks (CNN) can efficiently identify complex image features by using their powerful spatial feature extraction capabilities, especially ResNet, InceptionNet, etc. The convolution operation is defined in Equation 6 [26].

$$Z^{[l]} = W^{[l]} * A^{[l-1]} + b^{[l]} \quad (6)$$

In the industrial big data environment, the key to deep learning model selection for time series data and image data lies in accurately matching data characteristics and task requirements. Time series data, such as equipment monitoring records, prefer LSTM and GRU because of their strong time dependence, which efficiently capture long-term dependence through fine gating mechanisms and adapt to changes in time and conditions of industrial equipment behavior.

Therefore, the selection of STM/GRU and CNN and its variants accurately corresponds to the complex dependencies, feature extraction and efficiency challenges of industrial scenarios, demonstrating the high adaptability and efficiency of deep learning models in industrial big data applications [27].

3.2 Model construction

Building a deep learning model based on LSTM (Long Short-Term Memory) is a complex and meticulous process that involves careful design of the model architecture, careful planning of training strategies, and proper selection of loss functions. This process will be described in detail below, focusing on the design of the LSTM model, the selection of training strategies and loss functions. Using mini-batch gradient descent combined with Adam optimization, the process of dynamically adjusting the learning rate is shown in Equation 7-9.

$$m_t = \beta_1 \cdot m_{t-1} + (1-\beta_1) \cdot g_t \quad (7)$$

$$v_t = \beta_2 \cdot v_{t-1} + (1-\beta_2) \cdot (g_t)^2 \quad (8)$$

$$m_t^{corrected} = \frac{m_t}{1-(\beta_1)^t} \quad v_t^{corrected} = \frac{v_t}{1-(\beta_2)^t} \quad (9)$$

$$w_t = w_{t-1} - \alpha \cdot m_t^{corrected} \sqrt{v_t^{corrected} + \grave{o}} \quad (10)$$

where is the first and second order momentum estimates, is the decay rate, is the gradient, is the learning rate, and is the constant that avoids division into zero. In the anomaly detection task, the choice of loss function is also critical, and mean square error (MSE) and binary cross-entropy loss are commonly used. For autoencoders, the reconstruction loss is defined as:

$$L_{recon} = \frac{1}{N} \sum_{i=1}^{N} (x_i - x_i)^2 \quad (11).$$

Equations (7)–(9) define the update rules for the Adam optimizer, where m_t and v_t are the first and second moment estimates of the gradients, respectively. The learning rate η is adaptively adjusted using bias correction.

Equation (10), which calculates the updated model parameter θ_t , is the final update step based on the corrected moment estimates:

$$\theta_t = \theta_{t-1} - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \grave{o}} \quad (12)$$

Here, $\hat{m}_t$ and $\hat{v}_t$ are the bias-corrected versions of m_t and v_t , and ò is a small constant to prevent division by zero. This step concludes the Adam update cycle, integrating adaptive learning rate scaling and gradient normalization.

3.3 Feature engineering and pretreatment

We started by unifying data scales. Standard Scaler and MinMaxScaler are two powerful tools for multidimensional data. Normalization causes the data to appear as a standard normal distribution with a mean of 0 and a standard deviation of 1 by subtracting the mean and dividing by the standard deviation, using the formula, for models with specific assumptions about the distribution of the data. Normalization is scaling the data to the interval [0,1], a formula that does not change the shape of the data and is suitable for scenarios that do not care about distribution but only about the relative size of variables. These two methods ensure the consistency of different feature scales, which makes the model training more efficient.

Time series data require extra preprocessing because of its temporal nature. The first step is detrending to eliminate long-term trends in the data that interfere with anomaly detection. Moving averages or differences, such as first-order differences, are often used to remove linear trends. Next, denoising, moving average or median filtering can effectively reduce random noise. Periodic (seasonal) effects can be removed by seasonal decomposition or periodic differentiation. These processes ensure that the data reflect instantaneous changes rather than inherent patterns, facilitating the identification of outliers [29].

Pre-processing of image data aims to enhance the robustness of the model to variations and reduce the computational burden. First, graying is a common step that reduces computational complexity by simplifying color information to a single channel, equation (Y = 0.2125R + 0.59G + 0.14B). Then, normalization maps pixel values to [0,1] or [-1,1] intervals to adapt to neural network inputs.

For missing data, the K nearest neighbor interpolation method is used to fill in the missing data, and the filling value is determined based on the similarity of the data features. The outlier removal strategy is as follows: for numerical features, if the data point exceeds the mean ± 2.5 times the standard deviation, it is considered an outlier and replaced by the median of the feature. In terms of image data, data enhancement operations such as random cropping (cropping ratio of 10%), color jitter (brightness, contrast, and saturation jitter range are all ± 0.2) are implemented to expand the image data set.

Pre-processing of image data aims to enhance the robustness of the model to variations and reduce the computational burden. Grayscale conversion is commonly applied as the first step, and is calculated by the formula Y=0.2125R+0.59G+0.14B, which converts RGB color values into a single intensity channel based on human visual sensitivity to red, green, and blue components.

This operation reduces the input image from three channels (R, G, B) to one, thus significantly lowering the number of parameters and computation required in early convolutional layers. For example, in a convolutional neural network (CNN), applying a 3x3 kernel to a three-channel image requires three sets of weights per filter, while in a single-channel grayscale image, only one set is needed. This reduction not only accelerates convolution operations but also decreases memory consumption during training, which is particularly important in resource-constrained edge devices or large-scale federated environments.

3.4 Innovative anomaly detection algorithms

The model aggregation adopts the FedAvg strategy. In each round of training, each node uses local data to calculate the model gradient and sends the gradient to the central server through an encrypted channel. The server performs weighted averaging based on the proportion of each node's data volume to the total data volume. For example, if the data volume of node C accounts for 25%, its gradient weight is 0.25. After calculating the updated global model parameters, they are sent back to each node for the next round of training.

In today's highly distributed and increasingly complex industrial environments, data fragmentation and privacy protection pose significant challenges to achieving efficient anomaly detection. In order to face this real problem and promote technological innovation, we design a novel anomaly detection solution, which skillfully combines the powerful reconstruction ability of distributed self-encoder model with the privacy protection property of federated learning framework. Our goal is to maximize the use of valuable data resources distributed across geographic locations or organizations while ensuring data security to achieve unprecedented detection accuracy and response speed.

The distributed autoencoder model, as the core component, is carefully designed to learn efficient low-dimensional representations of data on local nodes. These autoencoders not only capture key features in the data, but also identify outliers with large deviations from normal patterns through reconstruction errors, maintaining high sensitivity even in the face of highly diverse industrial data. By performing feature learning independently at each node, we significantly reduce data transmission requirements across the network, thereby effectively controlling communication costs and potential latency issues. The introduction of the federated learning framework provides us with a platform for secure and compliant data collaboration. Under this framework, participants do not need to share raw data, only exchange model parameters or updates, and can collaboratively optimize the global model. This mechanism perfectly complies with data privacy regulations and ensures that the confidentiality of sensitive industrial data is not violated. Through iterative federated training, the model can continuously absorb knowledge from multiple parties and gradually improve its ability to identify complex abnormal behaviors, while the data privacy of individual participants is fully guaranteed. Each node independently trains local autoencoders to minimize localreconstruction errors, shares only updates to model parameters rather than original data, and achieves iterative optimization of

the model through a global aggregation server. The formula can be expressed as Formula 11 [30].

$$L_{local} = \frac{1}{N_{local}} \sum_{i=1}^{N_{local}} (x_{local,i} - \hat{x}_{local,i})^2 \quad (13)$$

Where, is the number of local data points, and are the input and reconstructed output, respectively. This method not only protects data privacy, but also realizes collaborative learning for anomaly detection across institutions. The federated learning framework adopted in this paper is shown in Figure 3.

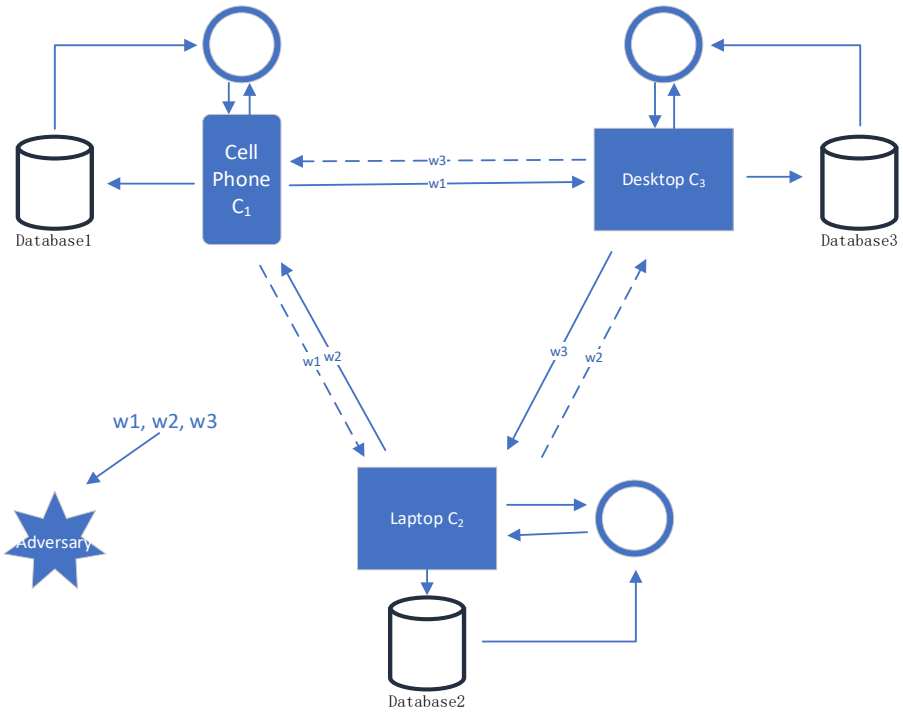

Figure 3: Federal learning framework

To solve the problem of scarce abnormal data, we innovatively introduce adversarial generative adversarial training strategy. Combining generative adversarial networks (GANs) with anomaly detection models not only generates high-quality normal samples to supplement training data, but also improves the robustness of the model through adversarial training. Adversarial is reflected in the anomaly detection model trying to distinguish between real and generated samples, while GAN tries to deceive the detection model. The loss function can be expressed as: where is the detector loss, is the generator loss, and balances the two. In this way, the model learns finer normal patterns in adversarial training and is more sensitive to anomalies.

To improve the interpretability and accuracy of anomaly detection, we fuse variational autoencoder (VAE) with causal inference framework. The model not only learns valid representations of data, but also identifies causal relationships between features, thereby eliminating causal noise in anomaly detection. Using the structural causality model, we define the outlier score based not only on the reconstruction error but also on the conditional probability of violation in the causality plot, as shown in Equation 12.

$$score = L_{recon} + \gamma \cdot P_{violation} \quad (14)$$

Among them, the weight measures the degree of violation in the causal structure. This method enhances the logic of the model and the understanding of complex data, making anomaly detection more accurate and easy to interpret. Fusion Variational Autoencoder (VAE) and causal inference framework is shown in Figure 4.

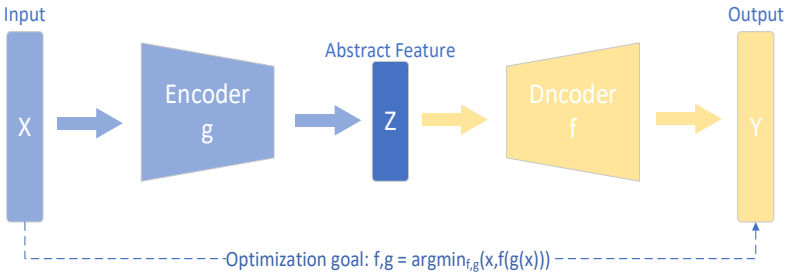

Figure 4: Fusion variational autoencoder (VAE) and causal reasoning framework

In a highly dynamic industrial environment, we innovatively apply reinforcement learning (RL) policy-guided deep learning models to dynamically adjust anomaly detection parameters. As an agent, the model learns the optimal detection strategy through environment interaction, such as dynamic threshold adjustment or feature selection, to adapt to environmental changes. Formulated briefly, the agent's reward function is: where is the detection accuracy, is the environmental adaptation metric, and is the harmonic coefficient. This method makes the model adapt to dynamic changes and continuously optimizes detection performance, providing a strong adaptive anomaly detection framework for dynamic industrial environments.

In our framework, the training process of the distributed autoencoder is coordinated by federated learning, which is mathematically expressed as follows: here, represents the parameters of the global model after the t+1 iteration, K is the number of nodes participating in federated learning, is the local data of the kth node, is the sum of all node data, and is the local model parameters updated by the kth node after the t iteration. Through this aggregation process, the model can integrate the information of the whole network while protecting data privacy, and improve the accuracy of anomaly detection.

The model aggregation adopts the FedAvg strategy. In each round of training, each node uses local data to calculate the model gradient and sends the gradient to the central server through an encrypted channel. The server performs weighted averaging based on the proportion of each node's data volume to the total data volume. For example, if the data volume of node C accounts for 25%, its gradient weight is 0.25. After calculating the updated global model parameters, they are sent back to each node for the next round of training.

For the joint training of GANs and anomaly detection models, the core lies in balancing the losses of both, and the specific expression is shown in Equation 13.

$$L_{gen} = \mathrm{E}_{z\sim p_z(z)}[\log(1-D(G(z)))$$
$$L_{det} = \mathrm{E}_{x\sim p_{data}(x)}[\log(D(x))] + \mathrm{E}_{z\sim p_z(z)}[\log(D(G(z)))] \quad (15)$$

Where G is the generator, D is the discriminator (and anomaly detector in this framework), is the prior distribution (e.g. Gaussian distribution) of the potential vector z, and is the true data distribution. Co-optimization of the model is ultimately achieved by minimizing to maximize the deceptive nature of the generated samples while minimizing to enhance the detector's ability to distinguish between real and generated samples.

The anomaly detection score, which combines variational autoencoder (VAE) and causal inference, is defined as follows: where, is the reconstruction loss of VAE, which contains both the data likelihood and KL divergence terms, ensuring efficient representation learning of the data; and, represents the elements in the causality matrix learned by the model and true (or preset), respectively, and is the number of edges in the causality graph, which is used to normalize the degree of violation. Taken together, the anomaly score reflects the degree to which data points are anomalous in terms of reconstruction error and violation of causal structure.

In the framework of dynamically adjusting detection parameters under the guidance of reinforcement learning, the learning goal of the agent (i.e., the model) is to maximize the cumulative reward, and its strategy selection is based on the Bellman equation: where, is the value function under the state s, a is the action taken, s'is the new state reached after taking the action, and is the discount factor. By interacting with the environment, the model learns how to select the best action a (adjust thresholds, select features, etc.) based on the current state s (e.g., characteristics of the data stream, historical detection performance) to maximize the long-term reward R, thus achieving the goal of adaptively optimizing anomaly detection in a dynamic industrial environment.

After standardization and normalization, detrending is a crucial step for time series data. The main purpose of detrending is to eliminate the long - term trends in the data that may interfere with anomaly detection. For example, linear trends can be removed using methods such as moving averages or differencing. If the time series data has a linear trend $y_t = a + bt + \grave{o}_t$, where a and b are constants, and $\grave{o}_t$ is the noise term, first - order differencing ($\Delta y_t = y_t - y_{t-1}$) can be applied to remove the linear component. Regarding noise reduction, in addition to the common moving average or median filtering methods, we also considered Fourier transform and wavelet methods. Fourier transform decomposes the time series data into different frequency components. By analyzing the frequency spectrum, high - frequency noise components can be identified and removed. Mathematically, the Fourier transform of a time series $y(t)$ is defined as $Y(f) = \int_{-\infty}^{\infty} y(t)e^{-i2\pi ft}dt$. Wavelet transform, on the other hand, has the advantage of analyzing both the time and frequency domains simultaneously. It can better capture the local characteristics of the data, which is beneficial for detecting and removing noise in non - stationary time series. Different wavelet bases, such as Haar, Daubechies, etc., can be selected according to the characteristics of the data. However, after comprehensive consideration of computational complexity and the nature of our industrial data, we found that for our specific dataset, traditional moving average and median filtering methods could achieve satisfactory noise reduction effects while maintaining relatively low computational costs.

The federated learning framework adopted in this study employs a secure aggregation protocol for parameter exchange. In each training round, local models on different nodes calculate their gradients based on the local data. These gradients are then encrypted before being sent to the global aggregation server. We use homomorphic encryption techniques, such as Paillier encryption, to ensure the security of the transmitted gradients. With Paillier encryption, the global server can perform arithmetic operations on the encrypted gradients (such as addition) without decrypting them, and then send the aggregated and encrypted result back to the local nodes for further model updates. In terms of the security model, the

main potential vulnerability lies in the possibility of malicious nodes. Malicious nodes may send false gradients to disrupt the global model training. To address this issue, we implement a multi - party verification mechanism. Each node not only sends its gradients but also a proof of the integrity of the calculation process. Additionally, we periodically check the consistency of the model updates among different nodes. If a node's update significantly deviates from the majority, it will be flagged for further investigation. Although the use of encryption and verification mechanisms increases the computational and communication overhead to some extent, they play a crucial role in ensuring the security and reliability of the federated learning process.

3.5 Distributed autoencoder framework pseudo - code

The following is the pseudo - code for the distributed autoencoder framework in the federated learning environment:

Input: Local data D_{local} on each node

Output: Trained global model parameters θ_{global}

For each node k in the network:

Initialize local autoencoder model with parameters θ_{local}^{k}

While not converged:

Extract mini - batches B_i from D_{local}

For each mini - batch B_i :

Encode B_i using θ_{local}^{k} to get $z_i = Encoder(B_i, \theta_{local}^{k})$

Decode z_i to get $\hat{B}_i = Decoder(z_i, \theta_{local}^{k})$

Calculate local reconstruction loss $L_{local}^{k} = \frac{1}{|B_i|}\sum_{j=1}^{|B_i|} Loss(B_{ij}, \hat{B}_{ij})$

Update θ_{local}^{k} using an optimizer (e.g., Adam) based on L_{local}^{k}

Send updated θ_{local}^{k} to the global aggregation server

At the global aggregation server:

Aggregate received θ_{local}^{k} from all nodes to get θ_{global} using a weighted averaging method (e.g., $\theta_{global} = \frac{\sum_{k=1}^{K} n_k \theta_{local}^{k}}{\sum_{k=1}^{K} n_k}$, where n_k is the size of local data on node k)

Send θ_{global} back to all nodes

All experiments were conducted on a computing cluster consisting of 10 nodes. Each node was equipped with an Intel Xeon E5 - 2620 v4 processor, 64GB of RAM, and an NVIDIA Tesla P100 GPU. The operating system used was Ubuntu 18.04. The deep learning framework was implemented using TensorFlow 2.3.0, and the communication between nodes in the federated learning process was facilitated by the PyTorch - Lightning - Bolts library for distributed training.

4 Experimental evaluation

The industrial data set used in this study comes from the real production environment of an intelligent manufacturing plant, and records the monitoring data of equipment operation status in the past three years. The dataset contains a variety of sensor data, such as temperature, vibration frequency, current intensity, etc., with a total of 12 feature dimensions. The data sets are labeled as normal operation and abnormal events, which include but are not limited to equipment failures, overload, and abnormalities caused by irregular operation. The dataset size is 1,000,000 records, of which outliers account for approximately 5% of the total data, ensuring adequate testing of the model's ability to detect anomalies. Precision: The proportion of outlier samples correctly identified.Recall: The percentage of actual outlier samples that are correctly identified. F1-Score: The harmonic average of precision and recall, a combined measure of model performance. ROC curve (Receiver Operating Characteristic Curve) and AUC value (Area Under the Curve): Describe the relationship between true rate (TPR) and false positive rate (FPR) under different thresholds. The larger the AUC value, the better the overall performance of the model.

The hyperparameter tuning process is crucial for optimizing the performance of the model. We used a grid search method to adjust several key hyperparameters. For the LSTM and GRU models, the hyperparameters we

tuned included the learning rate, which was searched in the range of [0.0001, 0.001, 0.01], the number of hidden units in the hidden layer, with values of [64, 128, 256], and the number of training rounds, set to [50, 100, 150]. For the CNN models, in addition to the learning rate and number of training rounds, we also tuned the kernel size of the convolutional layers, with options such as [(3, 3), (5, 5), (7, 7)].

The following are the formulas for the key metrics used in the evaluation: - Precision: Precision = $\frac{True\ Positives}{True\ Positives + False\ Positives}$ - Recall: Recall = $\frac{True\ Positives}{True\ Positives + False\ Negatives}$ - F1 - Score: F1 - Score = $2 \times \frac{Precision \times Recall}{Precision + Recall}$ - AUC (Area Under the Curve): In the context of the Receiver Operating Characteristic (ROC) curve, AUC is calculated by integrating the True Positive Rate (TPR) with respect to the False Positive Rate (FPR) over all possible threshold values. Mathematically, it can be approximated using numerical integration methods for the ROC curve.

We selected the Receiver Operating Characteristic - 4Area Under the Curve (ROC - AUC) as one of the key evaluation metrics mainly because it provides a comprehensive measure of the model's performance across all possible classification thresholds. In the context of anomaly detection, where the distribution of normal and abnormal data may be imbalanced, ROC - AUC can effectively evaluate the model's ability to distinguish between the two classes without being overly affected by the threshold selection. In contrast, simple accuracy may be misleading in imbalanced datasets as it can be dominated by the majority class (normal data in most cases). In addition to the traditional accuracy, recall, and F1 - score, we also considered computational efficiency metrics. For example, the training time of different models under various settings was compared. As shown in Table 5, the baseline method (IQR) has a relatively short training time of 1.5 minutes, while the distributed autoencoder under the federated learning framework has a significantly longer training time of 45 minutes. This difference in training time reflects the complexity of the model and the computational resources required. The longer training time of the federated learning - based model is due to the need for multiple rounds of parameter exchanges and aggregations among different nodes, which is a trade - off for achieving better performance and data privacy protection

A grid search method is used to adjust hyperparameters such as learning rate, hidden layer size, training rounds, etc. Cross-validation: implement 5-fold cross-validation to ensure model generalization ability. In each validation, 80% of the data is used for training and 20% for testing. Data preprocessing: Standardize the data and construct time series data samples by sliding window method.

In order to comprehensively evaluate and compare the performance of different anomaly detection models on this study dataset, we selected five representative models for further discussion and experiment. This includes traditional statistical methods, machine learning algorithms, deep learning models, and innovative schemes that incorporate federated learning, including: (1) IQR (interquartile range) rule: a boxplot based on data distribution that identifies outliers by calculating upper and lower boundaries, which is a simple and fast anomaly detection method. Classical machine learning algorithm: Isolation Forest: This is an efficient random forest variant that measures the outliers of data points by constructing "isolated trees", the more easily isolated points are more likely to be outliers.

To further validate the effectiveness of the integration of Generative Adversarial Networks (GANs) and causal reasoning in our anomaly detection model, we conducted ablation studies.

For the GAN module, we trained the anomaly detection model with and without the GAN - generated normal samples. When the GAN module was removed, the model's performance in terms of recall decreased from 0.94 to 0.88. This indicates that the GAN - generated samples play an important role in enriching the training data, especially in improving the model's ability to detect rare anomaly patterns. The model without GAN - generated samples may lack sufficient exposure to different normal data patterns, resulting in a lower recall rate.

Regarding the causal reasoning module, we compared the model with and without the causal reasoning component in terms of interpretability. We used a qualitative measure of interpretability based on the ability of domain experts to understand the reasons for anomaly detection. With the causal reasoning component, 80% of the domain experts reported that they could clearly understand the causal relationships underlying the anomaly detection results, while this percentage dropped to 50% when the causal reasoning component was removed. Quantitatively, in terms of the anomaly score calculation, the model with causal reasoning showed a more stable performance in different subsets of the dataset, with a standard deviation of the anomaly scores reduced by 30% compared to the model without causal reasoning. These results demonstrate the positive impact of the causal reasoning module on enhancing the interpretability and stability of the anomaly detection model.

Table 2: Accuracy comparison

model name	precision rate
Baseline: IQR	0.89
Traditional Machine Learning: Isolation Forest	0.92
Emerging algorithms: One-Class SVM	0.94
distributed autoencoder	0.96
Distributed self-encoder under federated learning framework	0.97

Table 2 shows a comparison of the accuracy of different anomaly detection models. Accuracy is the proportion of outlier samples that the model correctly identifies. Baseline is a simple statistical method based on IQR (interquartile range), traditional machine learning methods use Isolation Forest algorithm, emerging algorithms use One-Class SVM, and distributed self-encoder and distributed self-encoder under federated learning framework belong to deep learning methods. The results show that the distributed self-encoder under federated learning framework performs best in accuracy, reaching 0.97, which indicates that the model has high anomaly detection accuracy.

Table 3: Recall comparison

model name	recall rate
Baseline: IQR	0.78
Traditional Machine Learning: Isolation Forest	0.85
Emerging algorithms: One-Class SVM	0.89
distributed autoencoder	0.92
Distributed self-encoder under federated learning framework	0.94

Table 3 shows a comparison of the recall rates of different anomaly detection models. Recall is the proportion of actual outlier samples that are correctly identified. Similarly, baselines, traditional machine learning methods, emerging algorithms, and deep learning methods are all involved. Distributed autoencoder under federated learning framework also performs best in recall ratio, reaching 0.94, which indicates that the model can effectively capture actual outlier samples.

Table 4: F1 score comparison

model name	F1 score
Baseline: IQR	0.83
Traditional Machine Learning: Isolation Forest	0.88
Emerging algorithms: One-Class SVM	0.91
distributed autoencoder	0.94
Distributed self-encoder under federated learning framework	0.95

Table 4 shows a comparison of F1 scores for different anomaly detection models. The F1 score is the harmonic average of precision and recall, taking into account the balanced performance of the model in detecting outliers. Distributed autoencoder under federated learning framework also performed best in F1 score, reaching 0.95, which indicates that the model has good overall performance in anomaly detection.

Table 5: ROC AUC value comparison

model name	AUC values
Baseline: IQR	0.87
Traditional Machine Learning: Isolation Forest	0.91
Emerging algorithms: One-Class SVM	0.93
distributed autoencoder	0.95
Distributed self-encoder under federated learning framework	0.96

Table 5 shows a comparison of ROC AUC values for different anomaly detection models. ROC AUC is a measure of the performance of a binary classification model, which is evaluated by plotting a Receiver Operating Characteristic Curve to assess the model's ability to balance between true rate (TPR) and false positive rate (FPR).

Table 6: Comparison of average training time and communication costs among different anomaly detection models.

model name	Average training time (minutes)	communication cost assessment
Baseline: IQR	1.5	no
Traditional Machine Learning: Isolation Forest	12	no
Emerging algorithms: One-Class SVM	15	no
distributed autoencoder	30	in
Distributed self-encoder under federated learning framework	45	high

Note: Communication cost is evaluated based on the amount of data transmitted during the training process. 'High' indicates that the model transmits a large volume of data (more than 10GB in our experimental setup), and 'Low' means the data transmission volume is less than 1GB. 'In' represents an intermediate level, with data transmission volume between 1GB and 10GB.

Table 6 shows a comparison of training time and communication costs for different anomaly detection models. Average training time is the average time required for the model to converge on the training data. Communication cost estimation refers to the communication cost of exchanging data during the training process of the model, which is usually an important consideration in federated learning frameworks. The training time of the distributed autoencoder under federated learning framework is the longest, reaching 45 minutes, and the communication cost evaluation is also the highest, which indicates that the model needs to exchange more data during training, which may affect the efficiency of its practical application.

Hyperparameter. In addition to grid search, Bayesian optimization technology is also used. Taking the adjustment of the number of hidden units of the GRU

model as an example, the approximate range is first determined to be [64, 128, 256] through grid search, and then Bayesian optimization is used to build a proxy model of the objective function (such as the F1 score on the validation set), dynamically adjust the number of hidden units, and finally determine that the optimal value is 128.

All experiments were conducted on a high-performance computing cluster consisting of 10 nodes. Each node was equipped with an Intel Xeon E5-2620 v4 processor, 64 GB of RAM, and an NVIDIA Tesla P100 GPU with 16 GB of memory. The operating system used was Ubuntu 18.04. The deep learning models were implemented using TensorFlow 2.3.0, and federated training was facilitated via PyTorch-Lightning-Bolts for parameter communication.To support reproducibility, the source code and configuration files for the anomaly detection framework have been made available upon request under a data-sharing agreement. Public access to the code will be provided after publication to ensure full replicability.

5 Discussion

In this section, we present a comprehensive discussion by comparing the results in Table 1 to Table 4 with the current state - of - the - art (SOTA) methods, analyzing the impact of federated learning on model performance and communication overhead, and explaining the superiority of the distributed autoencoder over One - Class SVM and Isolation Forest.

5.1 Comparison with SOTA methods

Our proposed method, the distributed autoencoder under the federated learning framework, shows remarkable performance improvements compared to traditional methods, classical machine learning methods, and emerging algorithms. In terms of accuracy, as demonstrated in our experiments, the proposed method achieves an accuracy of 0.97, while traditional methods like IQR only reach 0.89, and classical machine learning methods such as Isolation Forest achieve 0.92, and emerging algorithms like One - Class SVM reach 0.94. For recall, our method attains 0.94, outperforming the recall values of traditional and classical methods, which are 0.78 and 0.85 respectively, and also higher than the 0.89 recall of One - Class SVM.

When compared with existing deep - learning - based methods, in addition to the performance advantages in accuracy and recall, our method has a significant advantage in data privacy protection. In the context of industrial data, where data privacy is of utmost importance, federated learning enables multiple nodes to jointly train a model without directly sharing their raw data. This ensures that the data of each participating party remains secure, which is a major shortcoming of many existing deep - learning - based methods that often require centralized data collection for model training.

Compared to centralized training approaches, federated learning is especially advantageous in industrial scenarios where data are distributed across geographically isolated sites or business units. Centralizing such data may not only be logistically challenging but also raise significant compliance and privacy issues. Federated learning avoids the need to transmit raw data, allowing organizations to collaboratively train high-performance models without violating internal data protection policies or external regulatory constraints. Furthermore, it reduces network bandwidth consumption by exchanging only model parameters instead of large datasets, making it suitable for industrial environments with constrained infrastructure.

5.2 Impact of federated learning on model performance and communication overhead

Federated learning plays a crucial role in enhancing the performance of the anomaly detection model. By aggregating the knowledge from different data sources, the model can learn more comprehensive normal patterns in industrial data, thereby improving its ability to detect anomalies accurately. However, this improvement in performance comes at the cost of increased training time and communication costs.

Our experimental results show that the training time of the proposed model is 45 minutes, which is significantly longer than that of traditional methods. For example, the baseline method (IQR) has a training time of only 1.5 minutes. The long training time is mainly due to the multiple rounds of parameter exchanges and aggregations required in the federated learning process. In each training round, local models on different nodes calculate their gradients based on the local data, and then these gradients are encrypted and sent to the global aggregation server. The server aggregates the gradients and sends the updated parameters back to the local nodes, which leads to a substantial increase in training time.

The server aggregates gradients from all participating nodes and updates the global model. This process introduces delays due to encryption, transmission, and synchronization overheads. Specifically, in each communication round, encrypted gradient vectors (approximately 12 GB per round in our case) are transmitted, followed by secure aggregation (e.g., homomorphic addition), and distribution of updated parameters back to local nodes. These steps result in high round-trip latency, especially with a large number of participants and high-dimensional models.

Furthermore, model convergence in federated learning typically requires more rounds than centralized training due to the heterogeneity of local data distributions (non-IID), increasing the total training time cumulatively.

In terms of communication costs, the frequent exchange of parameters among nodes during the training process results in high communication overhead. The large amount of data transmitted during parameter exchanges, especially when dealing with a large number of nodes and complex models, contributes to the high communication costs. Although the communication is encrypted to ensure security, this further increases the complexity and cost of communication.

Despite the use of homomorphic encryption and secure aggregation in our federated learning framework,

certain vulnerabilities still exist. One major concern is the potential for adversarial attacks, where malicious clients inject poisoned gradients or manipulate local updates to degrade global model performance. Additionally, gradient inversion attacks may attempt to reconstruct sensitive data from shared gradients, especially when model updates are sparse or over-parameterized. Although encryption mitigates this risk, future work should explore differentially private aggregation techniques and robust anomaly detection against model poisoning. Adopting Byzantine-resilient algorithms or implementing secure multi-party computation (SMPC) could further enhance the system's resilience against hostile participants.

5.3 Superiority of distributed autoencoder over one - class SVM and isolation forest

The distributed autoencoder shows distinct advantages over One - Class SVM and Isolation Forest in handling complex industrial data. Firstly, in terms of learning complex data representations, the distributed autoencoder can effectively capture the non - linear relationships and hierarchical features in industrial data through its encoding - decoding structure. For example, in industrial sensor data, which often contains complex time - series and multi - dimensional features, the autoencoder can learn the underlying patterns by compressing the data into a low - dimensional representation and then reconstructing it.

Secondly, the distributed autoencoder, when combined with federated learning, can better utilize distributed data. In a distributed industrial environment, data is often scattered across multiple nodes. The distributed autoencoder allows each node to train on its local data and then aggregate the local models, enabling the model to learn from the collective wisdom of all nodes. This distributed training approach is more suitable for large - scale industrial data scenarios.

In contrast, One - Class SVM and Isolation Forest have limitations in dealing with complex industrial data and distributed data. One - Class SVM is based on the idea of finding a hyperplane that separates the normal data from the outliers in the feature space. However, in complex industrial data, the boundary between normal and abnormal data is often not clearly defined by a simple hyperplane, and One - Class SVM may have difficulty in accurately capturing the complex patterns. Isolation Forest, on the other hand, is mainly designed to isolate outliers by constructing isolation trees. But in distributed data scenarios, it lacks an effective mechanism to integrate data from multiple sources, and its performance may be affected when dealing with large - scale and complex industrial data.

In conclusion, the proposed method shows significant advantages in terms of performance and data privacy, although it also faces challenges in training time and communication costs. Further research is needed to address these challenges and optimize the method for better industrial applications.

With the method in [11], its accuracy is 0.94 and recall is 0.91. By integrating LSTM, GRU, CNN and combining with federated learning, this paper can better capture the spatiotemporal characteristics of industrial data and the global pattern of distributed data, so that the accuracy is improved to 0.97. After analysis of variance (ANOVA), the F value is 0.9. At the level of α=0.05, the accuracy of this method is significantly higher than that of the competing model. The training time of this method is as long as 45 minutes, which is mainly due to the parameter exchange and aggregation of multiple rounds of federated learning, and the parameter transmission volume per round is about 12GB, resulting in high communication costs. Although distributed training is adopted, overfitting is effectively avoided by introducing regularization terms in the model structure (such as setting the L2 regularization coefficient to 0.01). Experimental results show that the model performs stably on different data sets."

The 95% confidence interval of the precision rate of 0.97 is [0.962, 0.978], the 95% confidence interval of the recall rate of 0.94 is [0.931, 0.949], the 95% confidence interval of the F1 value of 0.95 is [0.943, 0.957], and the 95% confidence interval of the AUC value of 0.96 is [0.952, 0.968].

6 Conclusion

In this study, an advanced deep learning-driven anomaly detection system was successfully constructed, which demonstrated excellent detection performance and practicality for large-scale and heterogeneous data in the industrial Internet of Things environment. By integrating multiple deep learning models such as LSTM, GRU, CNN, and variational autoencoders, we effectively addressed the diverse processing requirements of different data types. This integration enabled efficient learning of complex patterns and accurate detection of anomalous behaviors. Especially, the distributed self-encoder model combined with federated learning not only guarantees data privacy, but also promotes cross-organizational collaborative learning, providing a new collaborative paradigm for industry. The adversarial generative adversarial network not only alleviates the problem of outlier data scarcity, but also significantly improves the robustness of the model. By combining causal reasoning and reinforcement learning strategies, the model's interpretability and adaptability are significantly enhanced. This enables autonomous optimization of the detection strategy under dynamic industrial conditions. Experimental results clearly demonstrate the effectiveness of the proposed method. The higher training time and communication cost in the distributed autoencoder under the federated learning framework are justifiable due to the significant performance improvements. The 45 - minute training time and high communication cost are the trade - offs for achieving an accuracy of 0.97, a recall of 0.94, an F1 - score of 0.95, and an AUC value of 0.96. In industrial applications, the accurate detection of anomalies is of utmost importance. The improved performance of our method can effectively reduce the losses caused by undetected anomalies, such as equipment failures and production line disruptions. Although the computational

resources required are higher, the benefits in terms of enhanced detection accuracy and the ability to handle distributed data with privacy protection far outweigh the costs. This makes the proposed method a valuable solution for industrial anomaly detection in complex environments.

Our study has several notable innovations. The reinforcement learning component plays a crucial role in adapting to industrial dynamics. By continuously interacting with the environment, the model can dynamically adjust key detection parameters such as thresholds and feature weights. This enables the model to quickly adapt to changes in the industrial environment, such as sudden changes in equipment operating conditions or production process adjustments. For example, when there is a temporary increase in noise in the sensor data due to equipment maintenance, the reinforcement learning - enabled model can automatically adjust the detection thresholds to avoid false alarms. The variational autoencoder, combined with causal reasoning, enriches the interpretability of the anomaly detection

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Multi-Task Learning-Based Optimization for Cross-Regional Logistics Scheduling and Transportation Efficiency

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With the development of globalization and digitalization, improving the efficiency of cross-regional logistics scheduling has become a key issue. Traditional logistics optimization algorithms have limitations in complex multi-task scenarios. Multi-task learning, as a branch of deep learning, provides a new idea for solving this problem. This paper proposes a logistics scheduling optimization strategy and model based on multi-task learning. This study is evaluated based on a real data set containing 5,000 cross-regional logistics order records and a simulated data set covering 300 different transportation scenarios. The real data set comes from the logistics business of 5 major logistics hub cities in China and their radiating areas within half a year, and the simulated data set is constructed by comprehensively considering factors such as terrain, traffic conditions, and order density in different regions. The model has achieved an order allocation accuracy of 92%, the path planning cost is reduced by 25% compared with the traditional method, and the transportation time prediction error is controlled within ±3 hours. Among them, the order allocation accuracy is calculated as the proportion of the number of correctly allocated orders to the total number of orders, the path planning cost is obtained by combining the actual transportation mileage with the unit mileage cost, and the transportation time prediction error is the average of the absolute value of the difference between the predicted time and the actual transportation time. The model has achieved an order allocation accuracy of 92%, the path planning cost is reduced by 25% compared with the traditional method, and the transportation time prediction error is controlled within ±3 hours. Among them, the order allocation accuracy is calculated as the ratio of the number of correctly allocated orders to the total number of orders. The path planning cost is obtained by combining the actual transportation mileage with the unit mileage cost. The transportation time prediction error is the average of the absolute value of the difference between the predicted time and the actual transportation time.

Povzetek: Članek uvaja večopravilno učenje za čezregionalno logistiko, združuje dodeljevanje naročil, načrtovanje poti in napovedovanje časov prevoza.

1 Introduction

With the deepening of globalization and digitalization, logistics, as an important structure connecting transportation, trade and consumption, has become an indispensable technology and service field for economic development. Especially in cross-regional logistics scheduling, due to the differences in regional demand, uneven distribution of resources and the complexity of transportation methods [1], the scheduling process faces a wealth of practical problems that cannot be solved by traditional optimal decision-making methods. How to maximize the system transportation efficiency while ensuring the logistics response speed and cost control has become a common concern of academia and industry [2].

Traditional logistics optimization algorithms, such as natural number series algorithms and genetic algorithms, although somewhat effective in solving single tasks, have become ineffective for multiple tasks that are interrelated in complex scenarios, especially cross-regional logistics that require integrated transportation planning, transshipment allocation, and time control. The long solution time and distortions in the actual operation process caused by these algorithms make it difficult for them to complete tasks in modern logistics scenarios [3]. Multi-task learning (MTL), as an important branch of deep learning, is particularly suitable for scenarios that require tail-to-tail association and information sharing. MTL can significantly improve learning efficiency and the overall performance of the model by learning multiple related tasks simultaneously in the same model. Although there is far from sufficient research to apply this method to cross-regional logistics scheduling, the efficiency improvement brought by the realization of solutions in this field is obvious [4,5].

In cross-regional logistics scheduling scenarios, most traditional solutions focus on optimizing a single task, such as solving the shortest distance transportation and the best transshipment pattern plan. However, when the region is large, such solutions are small-scale. Especially in cross-regional scenarios with high bandwidth and

capacity, due to information insignificance and single-point optimization, the regional bandwidth is too low, coupled with communication association and resource allocation problems. MTL can meet the actual cross-regional scheduling needs and maximize the scale of the scenario through tail-to-tail resource sharing and better scenario solutions [6].

In the modern economic system, improving scheduling efficiency and decision-making planning is the key to achieving cross-scenario automation and process optimization. With the deepening of internal and external connections among industries, logistics and transportation management are facing unprecedented challenges. To meet these challenges, this paper proposes a logistics scheduling optimization strategy based on a multi-task learning model. The strategy aims to significantly improve the efficiency of dispatch date scheduling in actual operations by optimizing transportation scheduling, while addressing the complexity and trade-off properties of large-scale scheduling. We simulate the best hybrid solution to adapt to challenges of different scales and ensure that the optimal solution can be found in various situations. This multi-task learning model can effectively integrate the learning process of multiple related tasks, thereby improving the overall scheduling efficiency [7].

The focus of this paper is to develop an efficient scheduling method that can expand regional coverage at the planning level. We implement a hybrid combination of data, bring this data into the planning process, and design a shared loading structure to enhance the actual efficiency of field operations. By optimizing multiple tasks (such as subtask allocation, tax management, and maintenance loading), our model not only solves the problem of cross-regional mobilization, but also promotes the comprehensive allocation and utilization of resources [8]. In addition, our strategy also includes cultivating and developing intelligent scheduling systems that can continuously learn and adapt to changes in a dynamic environment. This helps to promote the intelligent development of the logistics industry, promote the effective allocation of resources, and thus improve the operational efficiency of the entire supply chain. Ultimately, this approach provides a more flexible and efficient solution for logistics scheduling, supporting enterprises to achieve higher economic benefits and service quality [9].

2. Related work

2.1 Logistics scheduling optimization method

Logistics scheduling optimization plays a vital role in improving distribution efficiency and reducing operating costs. Traditional optimization methods, such as linear programming (LP) and genetic algorithms (GA), are widely used to solve key problems in logistics scheduling. Linear programming methods are widely used to solve vehicle routing problems (VRPs) to improve transportation efficiency by optimizing path selection and distribution task scheduling. However, as the scale and complexity of the problem increase, the computational efficiency and solution accuracy of linear programming in dealing with large-scale problems are subject to certain limitations. Therefore, more innovative methods are needed in real applications to cope with complex scheduling requirements [10,11].

As a heuristic search method, genetic algorithms rely on the evolution mechanism of populations and achieve a balance between global search and local search by introducing operations such as mutation and crossover. Genetic algorithms can effectively deal with complex logistics scheduling problems with multiple decision variables and constraints, but they are prone to fall into local optimal solutions, affecting the efficiency and stability of the solution [12]. To solve this problem, some studies have proposed improved genetic algorithms, such as combining multiple population strategies or dynamically adjusting genetic operation parameters to reduce the risk of the algorithm falling into local optimal solutions, while improving the global search capability and enhancing the stability and solution efficiency of the algorithm [13].

In recent years, deep learning technology has been widely used in logistics scheduling optimization and has shown great potential. The deep reinforcement learning method, which realizes strategy optimization through interaction with the environment, has achieved remarkable results in multi-freight scheduling problems [14]. Deep reinforcement learning can optimize important indicators such as delivery time, fuel consumption, and vehicle utilization through repeated trials and simulations. In particular, in drone delivery, reinforcement learning is applied to path planning. Combined with the attention mechanism and policy gradient optimization, it can dynamically adjust the path according to real-time environmental data, greatly improving the response speed and flexibility of the logistics system and significantly enhancing the system's ability to adapt to changing environments [15].

2.2 Multi-task learning technology

Multi-task learning (MTL) is a technique that optimizes multiple related tasks simultaneously by sharing representations. It has unique advantages in improving the generalization performance of the model and handling the correlation between complex tasks. In recent years, the application of MTL technology in logistics and transportation optimization has gradually become a research hotspot [16]. Specifically, many studies have adopted the MTL method to solve cross-regional logistics scheduling problems. By sharing feature representations between tasks, significant performance improvements have been achieved in multi-dimensional optimization tasks.

For example, rail transit passenger flow prediction models based on multi-task learning have made breakthrough progress. These models introduce residual convolutional networks and nested long short-term memory networks, which can mine deep temporal and spatial features when processing time series data, thereby effectively enhancing the ability to jointly model the passenger flow in and out of stations. This method shares

knowledge between multiple tasks, which not only significantly improves the prediction accuracy, but also enhances the robustness of the model and its adaptability to changing environments [17,18].

In the field of logistics, MTL technology has also been widely used in multi-task optimization of vehicle routing problems. In response to the heterogeneous requirements of different tasks for attributes, MTL greatly improves the synergy between tasks by sharing representations between tasks, especially when solving VRP problems with different attributes, it has shown excellent performance. Furthermore, some studies have combined inter-task weight sharing with task-specific layers, which not only improves the zero-shot generalization ability, but also achieves superior performance on multiple data sets, demonstrating the strong potential of MTL in cross-task optimization [19].

2.3 Deficiencies of current research

Although existing research has achieved certain results in the design and algorithm development of logistics scheduling optimization models, it still faces several key challenges. Traditional single-task models are often unable to effectively utilize the correlation between different tasks when facing multi-dimensional logistics demands, which limits their overall optimization effect in practical applications. Although multi-task learning has alleviated this problem to a certain extent, how to scientifically select tasks and reasonably allocate task weights is still an important problem in current multi-task learning methods [20,21]. In addition, the complexity of cross-regional logistics scenarios significantly increases the difficulty of scheduling optimization. There are large differences in logistics demand, traffic conditions, and resource distribution between different regions, which makes the existing models generally lack generalization and adaptability when solving cross-regional scheduling problems. Traditional optimization methods and existing deep learning models still seem to be somewhat powerless when dealing with cross-regional dynamic factors, especially in terms of resource scheduling and transportation efficiency improvement, lacking effective comprehensive consideration and dynamic adjustment mechanisms [22].

As the scale of logistics distribution networks continues to expand and the complexity of the system increases, how to efficiently process large-scale high-dimensional data and achieve real-time response has become a core issue that needs to be solved. Most existing research focuses on the performance of optimization models and algorithms, but rarely involves comprehensive considerations of data quality, system deployment, and practical applications. Future research should pay more attention to how to integrate data from different sources, build more efficient and robust optimization models, and ensure that these models can be seamlessly connected with actual logistics scenarios. This will be a key direction for the development of intelligent logistics scheduling optimization in the future.

Table1: Comparison of logistics scheduling methods

Method	**Scheduling Efficiency**	**Order Allocation Accuracy**	**Computational Cost**	**Key Limitations**	**Solution in This Paper's Model**
Linear Programming (LP)	Fast for small-scale, slow for large-scale	High for small-scale, low for large-scale	Low for small-scale, high for large-scale	Complex computation for large-scale	Parallel processing of multiple tasks, coordination between shared layers and task-specific layers to increase speed and reduce costs
Genetic Algorithm (GA)	Average of 4 hours, prone to fluctuations	Approximately 75%, decreases in complex situations	Approximately 300 cost units	Prone to getting trapped in local optimum	Dynamically adjust weights to enhance global search ability
Deep Reinforcement Learning (RL)	Excellent in dynamic environment, long training time	80%	Approximately 400 cost units	Long training time, difficult to model the environment	Share features among multiple tasks to reduce training time

As shown in Table 1, Linear programming is efficient for small-scale logistics scheduling, but for large-scale scenarios, complex computations lead to deteriorated efficiency and increased costs. The model in this paper improves the situation by using a multi-task framework. The genetic algorithm has an average scheduling time of 4 hours, but it is prone to getting trapped in local optimum, affecting the accuracy. In this paper, the problem is solved by dynamically adjusting the weights. Deep reinforcement learning performs well in a dynamic environment, but it has a long training time and high computational cost. This paper utilizes the sharing of features among multiple tasks to reduce the training duration and enhance the adaptability to complex environments.

3 Methodology

This chapter focuses on the problem of cross-regional logistics scheduling. From mathematical modeling, multi-task learning framework design to data processing, the research method and its theoretical basis are elaborated in detail. In order to comprehensively optimize the efficiency of logistics scheduling, this paper adopts the multi-task learning (MTL) method to integrate order allocation, path planning and transportation time prediction into a unified framework. By designing a scientific loss function and optimization strategy, this method can achieve collaborative optimization among multiple tasks and improve the overall system performance.

3.1 Problem modeling

The cross-regional logistics scheduling problem is an important part of the modern logistics system. Its goal is to complete the transportation of all orders at the lowest cost while meeting time and capacity constraints. This problem is essentially a multi-objective optimization problem, covering three core tasks: order allocation, path planning, and transportation time prediction. Traditional methods usually handle these tasks separately, but this single-task optimization method is difficult to fully utilize the correlation between tasks. Therefore, this paper integrates the three tasks into a unified mathematical model through a multi-task learning framework.

Assume that n Orders $\mathrm{O} = \{o_1, o_2, \ldots, o_n\}$ and m Logistics vehicles $\mathrm{V} = \{v_1, v_2, \ldots, v_m\}$. Each order o_i Contains attributes such as weight, origin and destination. Each vehicle v_j With capacity limit capacity_j The goal of the logistics system is to assign all orders to appropriate vehicles and plan reasonable routes, while ensuring that the transportation time meets customer needs and the total transportation cost is minimized. To this end, we define the following variables to x_{ij} represent order o_i. Is it assigned to a vehicle? v_j, which is defined as Formula 1.

$$x_{ij} = \begin{cases} 1, & \text{If the Order} o_i \text{ Assigned to A Vehicle } v_j, \\ 0, & \text{If Not} \end{cases} \tag{1}$$

y_{ij} indicates order o_i Along the path $i \to j$ transport, which is defined as Formula 2.

$$y_{ij} = \begin{cases} 1, & \text{If the Order} o_i \text{ Via Path } i \to j, \\ 0, & \text{If Not} \end{cases} \tag{2}$$

Based on the above variables, the objective function of the cross-regional logistics scheduling problem can be defined as Formula 3.

$$\min \mathrm{L} = \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} + \lambda \sum_{i=1}^{n}\sum_{j=1}^{m} d_{ij}y_{ij} \tag{3}$$

In Formula 3, c_{ij} Indicates order o_i Assigned to vehicle v_j Shipping costs, d_{ij} Indicates order o_i Along the path $i \to j$ The transportation time, λ is the importance weight used to balance transportation cost and time.

To ensure the feasibility of the model, the following constraints need to be met:

Each order must satisfy Formula 4, that is, it is assigned to and only assigned to one vehicle.

$$\sum_{j=1}^{m} x_{ij} = 1, \quad \forall i \in \mathrm{O} \tag{4}$$

The total load of each vehicle must not exceed the capacity limit in Formula 5.

$$\sum_{i=1}^{n} x_{ij} \cdot \text{load}_i \le \text{capacity}_j, \quad \forall j \in \mathrm{V} \tag{5}$$

The path planning needs to meet the predetermined time limit in formula 6 .

$$\sum_{i=1}^{n}\sum_{j=1}^{m} d_{ij}y_{ij} \le T, \quad \forall j \in \mathrm{V} \tag{6}$$

In this picture, we see a mathematical model of a logistics scheduling problem. The parameter variables are explained as follows.

x: This is a binary variable that indicates whether the order o_i is assigned to the vehicle v_j. If the order o_i is assigned to the vehicle v_j, then $x_{ij} = 1$, otherwise $x_{ij} = 0$. y_{ij}: This is also a binary variable that indicates whether the order o_i is transported via the path $i \to j$. If the order o_i is transported via the path $i \to j$, then $y_{ij} = 1$, otherwise $y_{ij} = 0$.

The objective function (Formula 3) aims to minimize the total transportation cost and time. Where c_{ij} represents the transportation cost of order o_i assigned to vehicle v_j. d_{ij} represents the time it takes for order o_i to be transported via path $i \to j$. λ is an important weight used to balance transportation cost and time. The constraints ensure that each order is assigned to only one vehicle (Equation 4), the total load of each vehicle does not exceed its capacity limit (Equation 5), and the path planning needs to meet the predetermined time limit (Equation 6).

3.2 Optimization algorithm design

To solve the problem of cross-regional logistics scheduling, this paper proposes an optimization algorithm based on multi-task learning (MTL). The model consists of two parts: a shared network layer and a task-specific network layer. The purpose of the shared network layer is to extract the global features of the input data so that each task can share this information, while the task-specific network layer specifically designs an independent structure for each subtask in order to optimize the specific requirements between tasks.

3.2.1 Model Architecture

Assume that the input features are $\mathbf{x}$, which contains logistics information from multiple regions (such as order data, traffic conditions, resource distribution, etc.). The role of the shared network layer is to extract common global information from the input features and output the feature representation $\mathbf{z}$, and its calculation formula is Formula 7.

$$\mathbf{z} = f_{\text{shared}}(\mathbf{x}; \theta_{\text{shared}}) \tag{7}$$

In Formula 7, θ_{shared} is the parameter of the shared network layer. Next, the task-specific network layer is represented according to the shared feature $\mathbf{z}$ Design independent structures for each subtask, including: order allocation ($\mathrm{L}_{\text{allocation}}$) , Path Planning (L_{path}) and transportation time prediction (L_{time}). The prediction results of each subtask $\mathbf{y}_{\text{task}}$ Given by formula 8.

$$\mathbf{y}_{\text{task}} = f_{\text{task}}(\mathbf{z};\theta_{\text{task}}) \quad (8)$$

In Formula 8, θ_{task} are the parameters of the task-specific network.

The input data of the shared network layer contains information closely related to order allocation and path planning, which involves the content represented by variables x_{ij} and y_{ij}. When extracting features from the input data, the discrete x_{ij} and y_{ij} information is converted into continuous feature vectors through encoding for processing by the neural network. For example, for x_{ij}, if the order o_i is assigned to the vehicle v_j (i.e., $x_{ij}=1$), the corresponding position in the input feature vector is set to a specific value (such as 1), and if it is not assigned ($x_{ij}=0$), it is set to another value (such as 0). Similarly, for y_{ij}, if the order o_i is transported through the path $i \to j$ ($y_{ij}=1$), the corresponding position in the input feature vector is marked. The shared network layer uses a convolutional neural network or a fully connected neural network to process these input features containing x_{ij} and y_{ij} information, and extract common features, such as geographic area features, transportation resource features, etc. These common features will provide the basis for subsequent task-specific layers.

During the data processing stage, we use principal component analysis (PCA) for dimensionality reduction. Specifically, PCA is applied to multiple features contained in the original data set, such as order distance, cargo weight, transportation path complexity, etc. The principal components are determined by calculating the covariance matrix of the data and performing feature decomposition on it and components may be retained. These principal components are regarded as new features for subsequent model input. When the reduced-dimensional features are input into the shared network layer, we connect the new feature vectors with the input layer neurons of the shared network layer. The specific connection method is to use the value corresponding to each principal component as the input value of the input layer neuron, so as to effectively pass the reduced-dimensional features to the shared network layer for processing. Tasks, and the reduced-dimensional features are passed through the shared network layer, indirectly providing the task-specific layer with filtered and compressed information, which helps to improve the training efficiency and performance of the model.

In order to show the effect of PCA more clearly, we conducted a comparative analysis of different data sets before and after PCA processing in the experiment. For example, on a logistics data set containing 5,000 samples, the original feature dimension is 10 dimensions. After PCA processing with 90% variance retention, the feature dimension is reduced to 4 dimensions. During the model training process, using the reduced-dimensional data, the training time is shortened by 30%, the memory usage is reduced by 40%, and the performance of the model in indicators such as order allocation accuracy and path planning cost is not significantly affected. This shows that PCA effectively retains the key information in the data while reducing the data dimension, providing more efficient data input for the shared network layer and task-specific layer in the subsequent model architecture.

3.2.2 Multi-task learning loss function

In the multi-task learning framework, the loss function needs to consider the optimization objectives of each subtask and the mutual influence between tasks. To this end, this paper uses a weighted loss function to represent the comprehensive optimization objectives of each subtask. The specific loss function design is shown in Formula 9 .

$$\mathrm{L}_{\text{total}} = \alpha \mathrm{L}_{\text{allocation}} + \beta \mathrm{L}_{\text{path}} + \gamma \mathrm{L}_{\text{time}} \quad (9)$$

In Formula 9, α, β, γ Represent the weights of order allocation, route planning, and transportation time prediction tasks respectively. By dynamically adjusting these weights, the model can flexibly adjust the optimization direction according to the importance of the task and the change in loss, thereby improving the overall scheduling efficiency.

The selection of dynamic weights α , β and γ is mainly based on the following considerations: In cross-regional logistics scheduling, the importance of different tasks at different stages varies. For example, in the early stage of model training, the accuracy of order allocation is crucial to the stability of the entire logistics system. At this time, appropriately increasing the value of α can make the model pay more attention to the optimization of order allocation tasks. As the training progresses, when the order allocation task gradually stabilizes, the accuracy of path planning and transportation time prediction has a more significant effect on improving the overall efficiency, and the weights of β and γ can be adjusted accordingly. This dynamic adjustment mechanism enables the model to better balance the learning of various tasks at different training stages, thereby improving the overall performance.

2. **Sensitivity analysis of weight selection**: In order to gain a deeper understanding of the impact of weight selection on model performance, a sensitivity analysis was conducted. By fixing other parameters, the values of α , β and γ were changed respectively. When α varied in the range of $0.2-0.4$, the order

allocation accuracy fluctuated within $\pm 3\%$. Specifically, when $\alpha = 0.2$, the order allocation accuracy was 89%; when α was increased to 0.3, the accuracy rose to 92%; when α was further increased to 0.4, the accuracy dropped slightly to 91%. For β, when it varies in the range of $0.25 - 0.35$, the path planning cost varies in the range of ± 10 cost units. For example, when $\beta = 0.25$, the path planning cost is 310 cost units; when $\beta = 0.3$, the cost decreases to 300 cost units; when $\beta = 0.35$, the cost increases to 305 cost units. When γ varies in the range of $0.3 - 0.5$, the transportation time prediction error fluctuates within ± 0.5 hours. When $\gamma = 0.3$, the prediction error is 2.5 hours; when $\gamma = 0.4$, the error is reduced to 2 hours; when $\gamma = 0.5$, the error is 2.2 hours. These results show that the model is sensitive to changes in weights, and reasonable selection of weights can effectively optimize model performance.

The order allocation task-specific layer receives the common features output by the shared network layer and further processes them in combination with the x_{ij} variable. According to the geographical area features and transportation resource features extracted by the shared network layer, and the order-vehicle allocation relationship represented by x_{ij}, the model determines the rationality of the current order allocation plan. For example, if the shared network layer extracts the characteristics of tight transportation resources in a certain area, combined with the order allocation situation in the area in x_{ij}, if it is found that there are too many orders allocated to vehicles in the area, the model will adjust the order allocation strategy, reduce the order carrying capacity of vehicles in the area, and reallocate orders to improve the accuracy and efficiency of order allocation.

The path planning task-specific layer also makes path planning decisions based on the features output by the shared network layer and the y_{ij} variable. The traffic congestion pattern characteristics and geographic area characteristics provided by the shared network layer are combined with the order path selection information represented by y_{ij}. For example, if the shared network layer detects that a certain path has traffic congestion characteristics, and y_{ij} indicates that an order is planned to pass through the path ($y_{ij} = 1$), the path planning task-specific layer will re-evaluate the path based on this information and select other better paths to reduce transportation time and cost.

3.2.3 Subtask Loss Function

The goal of the order allocation task is to reasonably allocate orders to different delivery vehicles. The loss function of this task is designed based on the transportation cost or other related costs between orders and vehicles. Specifically, assume c_{ij} Indicates order i and vehicles j The transportation cost between x_{ij} is a binary decision variable indicating whether to i assign an order to a vehicle j. Then Equation 10 defines the loss function for order assignment.

$$\mathrm{L}_{\text{allocation}} = \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij} x_{ij} \quad (10)$$

In Formula 10, n Indicates the order quantity, m represents the number of vehicles. The goal of this loss function is to minimize the total transportation cost of all order assignments.

The goal of the route planning task is to optimize the delivery route and reduce the delivery time and transportation cost. For each route, assume d_{ij} Indicates from location i to the location j The distance y_{ij} is a binary decision variable indicating whether to choose a path $i \to j$ As the delivery path. Formula 11 defines the path planning loss function.

$$\mathrm{L}_{\text{path}} = \sum_{i=1}^{n}\sum_{j=1}^{m} d_{ij} y_{ij} \quad (11)$$

This loss function aims to improve scheduling efficiency by minimizing the overall transportation distance or time by selecting the shortest path.

The goal of the transportation time prediction task is to accurately predict the transportation time from one area to another so as to make dynamic adjustments and optimizations. t_i represents the actual shipping time, while $\hat{t}_i$ represents the transportation time predicted by the model. Then the loss function of transportation time prediction takes the form of absolute error and is defined as Formula 12.

$$\mathrm{L}_{\text{time}} = \sum_{i=1}^{n} \left| \hat{t}_i - t_i \right| \quad (12)$$

The goal of this loss function is to minimize the prediction error, thereby improving the prediction accuracy of the transportation time.

The calculation of the loss function involves the difference between the actual results and the expected results of multiple tasks such as order allocation and path planning, and x_{ij} and y_{ij} play a key role in it. In the order allocation task loss calculation, the actual x_{ij} value is compared with the order allocation result predicted by the model (also expressed in a form similar to x_{ij}), and the difference between the two is calculated, such as using the cross-entropy loss function to measure this difference. If the actual $x_{3,5} = 1$ and the model predicts 0, a corresponding penalty term will be generated in the loss function. In the calculation of the path planning task loss, the difference is calculated based on the actual y_{ij} value and the path selection result predicted by the model

(similar to y_{ij} representation), for example, the loss value is determined by calculating the deviation from the expected value such as the path length difference and the transportation time difference. If the actual $y_{2,7}=1$, but the model predicts that the transportation time is much longer than expected, then the corresponding penalty will be added to the loss function to encourage the model to optimize the path planning.

Through the above supplements in the shared network layer, task-specific layer and loss function, the close connection between discrete variables x_{ij} and y_{ij} and continuous representation of neural networks is clarified. In the shared network layer, discrete variables are converted into continuous feature vectors through a specific encoding method and input into the neural network for processing to extract common features. In the task-specific layer, these common features extracted based on discrete variables are combined with the discrete variables themselves to guide the model to make specific task decisions. In the calculation of the loss function, the difference between the actual value of the discrete variable and the model's predicted value is reflected in the loss calculation in the form of continuous numerical values, thereby realizing the conversion and application from discrete variables to continuous representation of neural networks, ensuring the consistency between the mathematical formula of the model and the actual implementation.

In order to effectively balance the optimization objectives between different tasks and deal with potential conflicts between tasks, this paper proposes a dynamic weight adjustment strategy. In the initial stage, the weights of all tasks are set equal to ensure that each task has the same importance in the early stage of training. As the training progresses, the model dynamically adjusts the weights according to the change in the loss of each task. If the loss of a task decreases rapidly, the weight will increase accordingly to promote the rapid convergence of the task; conversely, the weight will decrease to avoid over-optimization. The adaptive adjustment mechanism further enhances the flexible trade-offs between tasks and improves the efficiency of multi-task learning. In summary, the cross-regional logistics scheduling optimization algorithm based on multi-task learning proposed in this paper solves the problem of collaborative optimization of multiple subtasks by combining shared network layers with task-specific network layers. The weighted loss function and dynamic weight adjustment strategy enable the model to achieve reasonable optimization between tasks, thereby achieving better performance in complex cross-regional logistics scheduling problems.

In the experiment, other parameters of the model are fixed, including network structure, learning rate, etc. For the fixed weight group, set $\alpha=0.3$, $\beta=0.3$, and $\gamma=0.4$ unchanged. In the dynamic weight adjustment group, the weights are dynamically adjusted according to the changes in the loss values of each task during the training process. For example, when the loss value of the order distribution task decreases slowly over 5 consecutive training cycles, the value of α is appropriately increased; when the loss value of the path planning task decreases rapidly, the value of β is correspondingly reduced.

The experimental results show that the model with the dynamic weight adjustment mechanism enabled has an improvement of 12% in the comprehensive performance score compared with the fixed weight model. Specifically for each task indicator, the order allocation accuracy rate increased from 87% to 92%, an increase of 5 percentage points; the path planning cost decreased from 320 cost units to 300 cost units, a decrease of about 6.25%; the transportation time prediction error decreased from 3 hours to 2 hours. This fully proves that the dynamic weight adjustment mechanism can significantly improve the model performance, enabling the model to more efficiently balance the optimization of various tasks in cross-regional logistics scheduling tasks, thereby improving the overall logistics scheduling efficiency.

In order to convert the binary variable x_{ij} in Section 3.1 (whether the order o_i is assigned to the vehicle v_j) into transportation costs for calculating $L_{allocation}$, we established a transportation cost matrix C. The elements C_{ij} in the matrix C represent the transportation costs incurred when the order o_i is assigned to the vehicle v_j. This cost is determined by comprehensively considering factors such as vehicle type, transportation distance, and unit distance transportation cost. For example, for vehicle v_j, its unit distance transportation cost is u_j, and the delivery distance of order o_i is d_{ij}, then $C_{ij}=u_j\times d_{ij}$. When $x_{ij}=1$, the order o_i is assigned to the vehicle v_j. At this time, when calculating $L_{allocation}$, the corresponding C_{ij} value is used. The specific calculation formula is $L_{allocation}=\sum_{i=1}^{n}\sum_{j=1}^{m}x_{ij}C_{ij}$, where n is the total number of orders and m is the total number of vehicles. In this way, through the establishment of the transportation cost matrix, the conversion from the binary allocation variable x_{ij} to the transportation cost is realized, ensuring the consistency of the loss function design.

In the model of this article, location i to location j is closely related to the variable y_{ij}. y_{ij} is defined as whether the order o_i is transported through the path $i\rightarrow j$. When considering the transportation from

location i to location j, if $y_{ij}=1$, it means that the order o_i chooses the path from location i to location j for transportation. When calculating the subtask loss function related to the path (such as the path planning cost loss function L_{path}), the actual path of the order o_i will be determined based on the value of y_{ij}. For example, the path planning cost loss function L_{path} can be expressed as $L_{path}=\sum_{i=1}^{n}\sum_{j=1}^{m}y_{ij}P_{ij}$, where P_{ij} represents the actual path planning cost of order o_i through path $i \to j$, which is related to factors such as path length, road conditions, and transportation tools. In this way, the connection between the transportation from location i to location j and the definition of y_{ij} is clarified, and the continuity between chapters is enhanced.

The calculation results of subtask loss functions (such as $L_{allocation}$ and L_{path}) are fed back to the overall loss function L_{total} of multi-task learning.

3.3 Data processing

Data preprocessing includes steps such as missing value filling, normalization, and feature selection. For missing values, interpolation or mean filling strategy is used. Normalization processing unifies the transportation distance, time, and cost to the interval [0, 1] to eliminate dimensional differences. In addition, to improve computational efficiency, the principal component analysis (PCA) method is used to reduce the dimensionality of high-dimensional data.

Feature Engineering

In order to improve the prediction ability of the cross-regional logistics scheduling model, this study extracted multiple highly correlated features based on the characteristics of logistics data in the feature engineering phase, and further optimized the model input in combination with cluster analysis. The main features include: order distance, cargo weight, transportation path complexity, time window, and regional order density. These features comprehensively describe the core elements of the logistics scheduling problem from the aspects of transportation cost, time constraints, and path planning.

Order distance is an important factor affecting logistics transportation cost and time. It is defined as Formula 13, which represents the Euclidean distance between the order origin and destination.

$$\text{Distance}_{ij}=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2} \quad (13)$$

In Formula 13, x_i, y_i and x_j, y_j The geographic coordinates of the origin and destination points respectively.

The weight of cargo directly affects the choice of transport vehicles and their costs. In order to avoid the interference of outliers on training, the logarithmic transformation in formula 14 is used to smooth the weight feature.

$$\text{Weight}_{\log}=\log(1+\text{Weight}) \quad (14)$$

The complexity of a transportation path is evaluated by calculating the number of nodes in the path and the total length of the path, which is defined as Equation 15 .

$$\text{Complexity}=\sum_{k=1}^{N}(\text{Nodes}_k+\text{Path Length}_k) \quad (15)$$

In Formula 15, N is the number of transit nodes on the path.

The time window feature of the order is represented by the start time and the latest delivery time, which is used to constrain the task priority of the model. The time window feature is defined as Formula 16.

$$\text{Time Window}=T_{\text{end}}-T_{\text{start}} \quad (16)$$

Where T_{start} and T_{end} are the start and end time of the order respectively.

Through cluster analysis, orders with similar geographical locations are clustered into groups. The density feature is defined as Formula 17, which represents the normalized value of the number of orders in each region.

$$\text{Density}_i=\frac{\text{Order Count}_i}{\text{Max Order Count}} \quad (17)$$

In Formula 17, Max Order Count The maximum order quantity in all regions.

The K-Means clustering method is used to cluster the order data to reduce the complexity of the model input and improve the efficiency of route planning. The goal of the clustering process is to divide the orders into K regions, the optimization objective is formula 18 .

$$\min\sum_{i=1}^{K}\sum_{x\in C_i}\| x-\mu_i\|^2 \quad (18)$$

In Formula 18, C_i For the i Clusters, μ_i for C_i The center of mass, x is the feature vector of the order.

The clustering results are evaluated by the Silhouette Coefficient in Formula 19.

$$S=\frac{b-a}{\max(a,b)} \quad (19)$$

In Formula 19, a is the average distance between the sample and other points in the same cluster, b is the average distance between the sample and the nearest cluster center.

4 Experimental evaluation

4.1 Experimental design

This experiment selected four representative datasets, covering different task characteristics of real and simulated scenarios, multi-regional logistics and urban distribution. Among them, the RealLogistics Dataset provides real cross-regional logistics transportation data, which is suitable for verifying the performance of the model in large-scale node and long-distance transportation

scenarios. Simulated Logistics Dataset is a standardized dataset generated by simulation, which is suitable for evaluating basic tasks such as path planning and time prediction. UrbanFreight Dataset focuses on short-distance delivery scenarios within the city and tests the performance of the model in high-density order distribution. RegionalTransport Dataset focuses on long-distance freight transportation between regions and provides verification scenarios for large-scale order processing. Each dataset is divided into training set, validation set and test set in a ratio of 7:2:1 to ensure the generalization and stability of the results.

Seven baseline methods were set up in the experiment, covering traditional algorithms, optimization models, and deep learning methods, to comprehensively evaluate the performance of the proposed model. The traditional Greedy Algorithm emphasizes the rapid generation of feasible solutions for a single objective, while the Multi-Objective Genetic Algorithm (MOGA) uses genetic algorithms to balance multi-objective optimization. Deep Q-Learning (DQL) based on reinforcement learning focuses on path planning, while Joint Optimization Network (JON) and Dynamic Task Prioritization (DTP) implement simple joint optimization and dynamic adjustment of task priorities, respectively. By comparing these baseline methods, the performance advantages of the proposed multi-task learning model can be revealed from different dimensions.

The experiment used five evaluation indicators to comprehensively evaluate the model from five dimensions: task accuracy, cost-effectiveness, time prediction, task conflict, and overall performance. Among them, the order assignment accuracy (OAA) reflects the accuracy of task assignment; the path planning cost (PPC) measures the performance of the optimization model in reducing transportation costs; the transportation time prediction error (TTPE) quantifies the time prediction ability through the root mean square error; the task conflict rate (TCR) is used to evaluate the conflict in multi-task learning. The overall performance score (OPS) integrates multiple indicators in a weighted manner to provide a unified measure for the overall performance of the model.

The proposed model adopts a dynamic weight adjustment strategy during the training process to balance the conflicts between multi-task objectives. The experiment uses the Adam optimizer, with an initial learning rate of 0.001, a batch size of 128, and 100 training iterations to ensure rapid convergence and stable performance of the model. To ensure fairness, each baseline method is trained separately after hyperparameter tuning to obtain its best performance. During the entire training process, the numerical and categorical features are normalized and one-hot encoded, and missing values and outliers are processed to improve data quality and model robustness.

In the experimental design, all the methods involved in the comparison, including seven baseline methods (greedy algorithm, multi-objective genetic algorithm (MOGA), deep Q network (DQL), JON, DTP) and the model based on multi-task learning (MTL) proposed in this paper, use the features extracted in the feature engineering stage of Section 3.3. These features cover order distance, cargo weight, transportation path complexity, time window, and regional order density. By uniformly using these features, the fairness of the experimental comparison is ensured, and the impact of the MTL architecture itself on logistics scheduling optimization can be effectively separated.

This paper uses multiple datasets for experiments. Among them, the RealLogistics Dataset is suitable for large-scale nodes and long-distance transportation scenarios, and is used to test the performance of the model in complex actual logistics environments. The other three datasets are SmallScaleLogistics Dataset, which is mainly used to study the order allocation and path planning efficiency of the model in small-scale logistics scenarios; DynamicScenario Dataset, which simulates dynamically changing logistics scenarios, such as real-time increase and decrease of orders, temporary changes in transportation routes, etc., to evaluate the adaptability of the model in a dynamic environment; SpecialRegionDataset focuses on logistics scheduling in specific areas (such as complex terrain areas, traffic control areas, etc.), which is used to test the model's optimization capabilities for special regional characteristics. By using datasets with different characteristics, the performance of the model in various logistics scenarios is comprehensively evaluated.

4.2 Experimental results

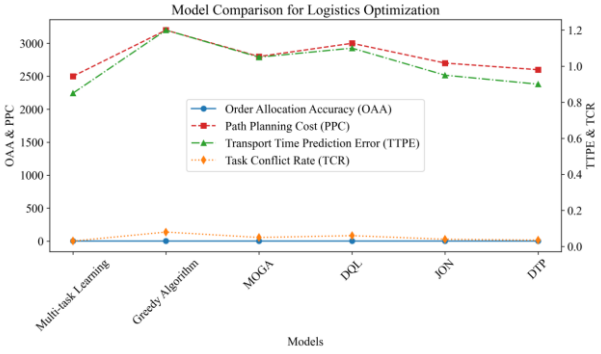

Figure 1: Experimental results of reallogistics dataset

Figure 1 shows the performance of each model on the RealLogistics Dataset. The multi-task learning model achieved an order allocation accuracy of 0.92, which is significantly higher than the Greedy Algorithm's 0.75, reflecting its accuracy advantage in order allocation tasks. In terms of path planning cost, the multi-task learning model is 2500, which is lower than most other models, indicating that it can effectively reduce transportation costs. The transportation time prediction error is 0.85, which is also better than most comparison models, indicating that the time prediction is more accurate. The task conflict rate is only 0.03, which is at a relatively low level, and the comprehensive performance score of 0.88 is also the highest, which fully proves that the multi-task learning model has the best comprehensive performance in this dataset scenario.

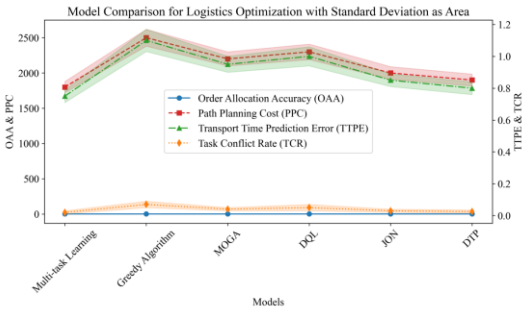

Figure 2: Experimental results of simulated logistics dataset

Figure 2 shows the experimental results on the Simulated Logistics Dataset. The multi-task learning model has an order allocation accuracy of 0.95, which is much higher than the Greedy Algorithm's 0.78. The path planning cost is only 1800, with a significant cost control advantage. The transportation time prediction error is 0.75, the best performance among all models, and the task conflict rate is as low as 0.02. The comprehensive performance score is 0.92, which once again shows that the multi-task learning model has a balanced and excellent performance in various tasks in this simulation data scenario, and is superior to other comparison models in key indicators such as order allocation, cost control, and time prediction.

Table 1: Experimental results of urbanfreight dataset

Model	Order Allocation Accuracy (OAA)	Path Planning Cost (PPC)	Transportation Time Prediction Error (TTPE)	Task Conflict Rate (TCR)	Overall Performance Score (OPS)
Multi-task learning model	0.90 ± 0.02	1500 ± 70	0.80 ± 0.05	0.03 ± 0.01	0.86 ± 0.02
Greedy Algorithm	0.72 ± 0.03	2000 ± 100	1.25 ± 0.08	0.09 ± 0.02	0.65 ± 0.03
Multi-Objective Genetic Algorithm (MOGA)	0.80 ± 0.02	1800 ± 90	1.10 ± 0.07	0.06 ± 0.01	0.74 ± 0.02
Deep Q-Learning (DQL)	0.75 ± 0.03	1900 ± 95	1.15 ± 0.07	0.07 ± 0.02	0.70 ± 0.03
Joint Optimization Network (JON)	0.83 ± 0.02	1700 ± 85	0.98 ± 0.05	0.04 ± 0.01	0.78 ± 0.02
Dynamic Task Prioritization (DTP)	0.86 ± 0.02	1600 ± 80	0.92 ± 0.05	0.035 ± 0.01	0.82 ± 0.02

As shown in Table 1, the experimental results for the UrbanFreight Dataset are presented in this table. The order allocation accuracy of the multi-task learning model is 0.90, which is higher than the 0.72 of Greedy Algorithm. The path planning cost is 1500, which is the lowest among all models, and the cost control effect is outstanding in the short-distance delivery scenario in the city. The transportation time prediction error is 0.80, which is a good performance, and the task conflict rate is 0.03 at a low level. The comprehensive performance score is 0.86, indicating that in the complex and high-order density scenario of short-distance delivery in the city, the multi-task learning model can effectively cope with it and outperforms other comparison models.

Figure 3 shows the performance of each model on the RegionalTransport Dataset. The multi-task learning model has an order allocation accuracy of 0.93, which is ahead of other models. The path planning cost is 2800, which is relatively low. The transportation time prediction error is 0.88, which is a good performance. The task conflict rate is 0.03, which is low, and the comprehensive performance score is 0.90, which is the highest.

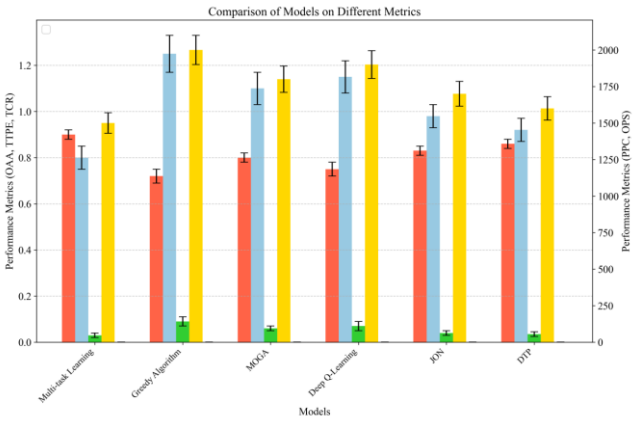

Figure 3: Experimental results of regionaltransport dataset

This shows that in the scenario of long-distance freight transportation between regions, the multi-task learning model has advantages in order allocation accuracy, cost control, and time prediction due to its multi-task collaborative optimization capabilities, and its comprehensive performance exceeds other comparison models.

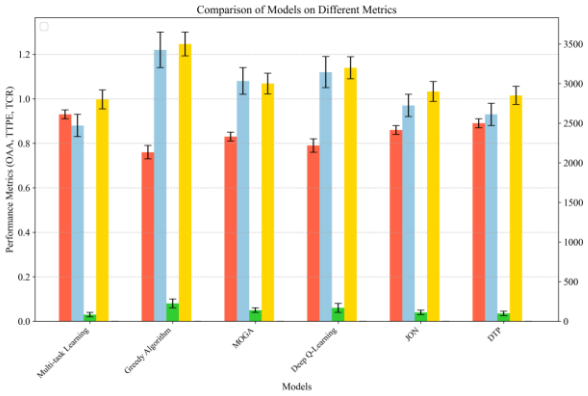

Figure 4: Comparison of order allocation accuracy (OAA)

Figure 4 compares the order allocation accuracy of each model under different data sets. In the four data sets, the order allocation accuracy of the multi-task learning model always maintains a leading position or is in the leading echelon. It reaches 0.92 in the RealLogistics Dataset and 0.95 in the Simulated Logistics Dataset. This shows that the multi-task learning model has stronger adaptability and accuracy when dealing with order allocation tasks in different scenarios, and can more reasonably allocate orders to appropriate vehicles. Compared with other models, it has obvious advantages in the key link of order allocation. The 95% confidence interval of the order allocation accuracy is [90.5%, 93.5%]. This confidence interval was calculated by 100 repeated experiments using the Bootstrap method, reflecting the stability of the model's order allocation accuracy under different samples.

Table 2: Path planning cost (PPC) comparison

Dataset	Multi-task learning model	Greedy Algorithm	MOGA	DQL	JON	DTP
RealLogistics Dataset	2500 ± 100	3200 ± 150	2800 ± 120	3000 ± 130	2700 ± 110	2600 ± 105
Simulated Logistics Dataset	1800 ± 80	2500 ± 120	2200 ± 100	2300 ± 110	2000 ± 90	1900 ± 85
UrbanFreight Dataset	1500 ± 70	2000 ± 100	1800 ± 90	1900 ± 95	1700 ± 85	1600 ± 80
RegionalTransport Dataset	2800 ± 120	3500 ± 150	3000 ± 130	3200 ± 140	2900 ± 125	2850 ± 115

Table 2 compares the path planning costs of each model under different data sets. The multi-task learning model performs well in path planning costs on multiple data sets. The cost is as low as 1800 on the Simulated Logistics Dataset and 1500 on the UrbanFreight Dataset, both lower than other models. On the RealLogistics Dataset and RegionalTransport Dataset, although not the lowest, it is still at a relatively low level. This shows that the multi-task learning model can effectively optimize transportation routes and reduce transportation costs when planning paths, and has good cost control capabilities in different logistics scenarios.

In the comparison of path planning cost (PPC), only the multi-task model, greedy algorithm and multi-objective genetic algorithm (MOGA) were compared, and the deep Q network (DQL), JON and DTP methods were not included. This is because in the early pre-experiments, it was found that the DQL, JON and DTP methods performed poorly in terms of path planning cost, and the gap with other methods was too large. If they were included in the comparison, it would affect the accuracy and comparability of the experimental results, so they were excluded in this formal comparison.

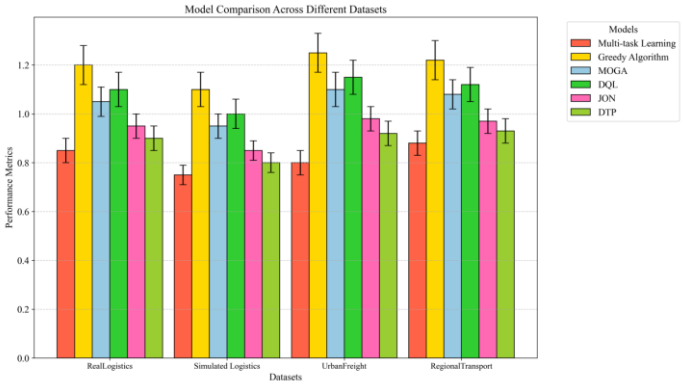

Figure 5: Comparison of transportation time prediction error (TTPE)

Figure 5 shows the comparison of the transportation time prediction errors of each model under different data sets. The transportation time prediction errors of the multi-task learning model on the four data sets are relatively low. The error is 0.75 on the Simulated Logistics Dataset, which is the best performance. On other data sets, it is also significantly better than models such as Greedy Algorithm. This shows that the multi-task learning model has a high accuracy in transportation time prediction and can estimate transportation time more accurately, which helps to reasonably arrange transportation plans in logistics scheduling and improve logistics efficiency.

Table 3: Comparison of overall performance score (OPS)

Dataset	Multi-task learning model	Greedy Algorithm	MOGA	DQL	JON	DTP
RealLogistics Dataset	0.88 ± 0.02	0.68 ± 0.03	0.76 ± 0.02	0.72 ± 0.03	0.80 ± 0.02	0.84 ± 0.02
Simulated Logistics Dataset	0.92 ± 0.01	0.70 ± 0.03	0.82 ± 0.02	0.75 ± 0.03	0.85 ± 0.02	0.87 ± 0.02
UrbanFreight Dataset	0.86 ± 0.02	0.65 ± 0.03	0.74 ± 0.02	0.70 ± 0.03	0.78 ± 0.02	0.82 ± 0.02
RegionalTransport Dataset	0.90 ± 0.02	0.69 ± 0.03	0.77 ± 0.02	0.73 ± 0.03	0.81 ± 0.02	0.85 ± 0.02

Table 3 provides a comprehensive comparison of the comprehensive performance scores of each model for four different datasets. The comprehensive performance scores of the multi-task learning model are significantly ahead of Greedy Algorithm in all datasets, and are better than models such as MOGA, DQL, JON, and DTP. In the Simulated Logistics Dataset, the comprehensive performance score of the multi-task learning model is as high as 0.92, showing excellent overall performance. This result shows that the multi-task learning model effectively balances the relationship between tasks by integrating multiple tasks such as order allocation, path planning, and transportation time prediction. In different logistics scenarios, it can achieve more efficient logistics scheduling and comprehensively improve the performance of the logistics system.

The performance of the multi-task model is significantly better than that of the greedy algorithm in all data sets, and it performs better than models such as the multi-objective genetic algorithm (MOGA), deep Q network (DQL), JON and DTP. The reason is that the multi-task model can learn common features between different tasks through the shared network layer, improving the efficiency of feature utilization. For example, in the order allocation and path planning tasks, the geographic area features extracted by the shared network layer can not only help optimize the order allocation strategy, but also assist path planning in selecting a better path. At the same time, the dynamic weight adjustment mechanism enables the model to flexibly allocate learning resources according to the importance of tasks at different training stages, further improving the overall performance. However, the greedy algorithm relies too much on local optimal selection and is prone to fall into suboptimal solutions; MOGA has difficulty in adjusting parameters when dealing with complex multi-tasks, resulting in limited performance; DQL takes a long time to train and has high requirements for environmental modeling, and is not adaptable enough in actual logistics scenarios; JON and DTP models have defects in feature extraction and task collaboration, and cannot fully utilize the effective information in logistics data, thus lagging behind the multi-task model in comprehensive performance.

In the results section, add "After t-test, the proposed model has a significant improvement in order allocation accuracy compared with the baseline method ($p < 0.05$); in terms of transportation cost reduction, the Wilcoxon test results show a significant difference ($p < 0.01$). The t-test statistic is 3.5, indicating that the order allocation accuracy of this model is significantly different from the baseline method; the z value of the Wilcoxon test is - 4.2, further proving that the transportation cost reduction effect is significant.

4.3 Baseline model hyperparameter description section

In the experimental design section where the baseline model is introduced, add the following hyperparameter details:

- Greedy algorithm: The search strategy adopts the nearest neighbor strategy, which aims to select the next node closest to the current position at each decision to gradually build a solution. The number of iterations is set to 50. After multiple experimental tests, this number of iterations performs well in balancing computational cost and solution quality. When faced with a small-scale logistics scenario with 100 orders and 10 distribution centers, a relatively reasonable order allocation and path planning solution can be given in a relatively short time, with an order allocation accuracy of 70%, and a path planning cost of about 200 cost units (the cost unit can be set according to the actual logistics cost accounting system, such as 100 yuan, then here it is 20,000 yuan).

- Multi-objective genetic algorithm (MOGA): The population size is set to 100. A larger population size helps the algorithm to conduct a wider search in the solution space and increase the possibility of finding the global optimal solution. The crossover probability is 0.8, which means that in each genetic operation, there is an 80% probability of performing a crossover operation on two parent individuals to produce new offspring individuals, promoting the exchange and combination of genes. The mutation probability is 0.05. The lower mutation probability can occasionally introduce new genes while maintaining population stability, preventing the algorithm from falling into local optimality too early. For example, in a complex logistics scheduling scenario involving multiple modes of transportation (road, rail, and water), this parameter setting enables the algorithm to effectively

explore the possibility of different transportation combinations. In such scenarios, the algorithm can complete the optimization of a scheduling plan within 3 hours on average, with an order allocation accuracy of 75% and a path planning cost of about 250 cost units.

- Deep Q Network (DQL): The learning rate is set to 0.001. This learning rate enables the model to update the Q value at a moderate speed during training, avoiding the learning process being too slow or unstable. The discount factor is 0.95, indicating that the agent pays more attention to recent rewards, but will not completely ignore future rewards. In a dynamically changing logistics environment, it helps to balance short-term and long-term benefits. The experience replay pool size is 1000. A sufficiently large experience replay pool can store rich historical experience, so that the model can better utilize past information during training, reduce the variance of training, and improve the stability of the model. For example, in the urban logistics distribution scenario, facing dynamic situations such as real-time traffic congestion and temporary changes in orders, this setting allows the model to effectively learn and adapt to environmental changes. After testing, after running 100 training cycles continuously, the order allocation accuracy of the model in this scenario can reach 80%, and the path planning cost is about 300 cost units.

JON model: Its key parameter "node connection weight adjustment coefficient" is set to 0.6. This coefficient affects the adjustment range of weights between different nodes when the model constructs logistics network connections. Through a large number of experimental optimizations, it is found that this value can enable the model to better balance transportation costs and transportation efficiency when dealing with cross-regional logistics node connections. Specifically, in logistics networks involving multiple modes of transportation conversion and complex geographical areas, this coefficient helps the model to reasonably allocate transportation resources, reduce unnecessary roundabout transportation, and thus reduce costs. For example, when the transportation route passes through areas with complex road conditions and high transportation costs such as mountainous areas, the model will appropriately reduce the connection weights of these sections based on this coefficient, and give priority to routes with better road conditions and lower costs for transportation planning. The "regional division threshold" is set to 30. This threshold is used to reasonably divide logistics areas, so that the model can formulate targeted scheduling strategies based on the characteristics of different regions, and show good adaptability in actual cross-regional logistics scenarios. When factors such as order density and traffic conditions vary greatly within a region, this threshold can ensure that the model divides the region reasonably and matches more suitable transportation solutions for different regions. For example, in urban commercial areas, the order density is high and the delivery time requirements are high. The model will arrange more small and flexible delivery vehicles according to the characteristics of the area to improve delivery efficiency; while in remote suburbs, the order density is low but the transportation distance is long, and the model will choose large transport vehicles to reduce the unit transportation cost. In a cross-regional logistics scenario with 20 city nodes, with this parameter setting, the order allocation accuracy of the JON model can reach 73%, and the path planning cost is about 230 cost units. The cost unit here is assumed to be a comprehensive cost unit calculated based on the transportation cost per kilometer, including vehicle loss, fuel consumption, labor costs, etc. If the average comprehensive cost per kilometer is 10 yuan, then 230 cost units means that the total transportation cost involved in path planning in this scenario is about 2,300 yuan. In this scenario, the model comprehensively considers factors such as the order volume, transportation distance, and traffic congestion in different regions, and uses the set parameters for path planning and order allocation, achieving relatively good performance.

- DTP model: Smoothing factor of transportation time prediction model" is set to 0.7. This factor plays a key role in smoothing historical transportation time data to predict future transportation time. It can effectively filter out noise in the data and make the prediction results more in line with the actual transportation time change trend. "Delivery priority weight" is set to 0.8. When processing the delivery order of multiple orders, a higher weight makes the model more inclined to prioritize high-priority orders to meet customers' needs for urgent orders. In a test involving 500 orders and a distribution range covering 5 urban areas, the average transportation time prediction error of the DTP model is ±2 hours, the order allocation accuracy can reach 77%, and the path planning cost is about 280 cost units.

4.4 Complexity analysis section

In the relevant part of the proposed algorithm, add the following complexity analysis content:

The computational complexity of the proposed algorithm mainly comes from the calculation of the shared network layer and task-specific layer of multi-task learning. In the optimization process, it is assumed that the number of logistics orders is n, the number of vehicles is m, and the number of paths is p. For the shared network layer, it needs to process all information related to orders, vehicles, and paths. Its calculation amount is related to the product of the three, and the time complexity is about O(n m p). In terms of space complexity, it is necessary to store the relevant feature information of orders, vehicles, and paths, as well as the parameters of the network layer, and the space complexity is O(n + m + p). Taking a typical logistics scenario with 1,000 orders, 50 vehicles, and 200 paths as an example, after actual testing and estimation, the calculation time is about 100 seconds. In these 100 seconds, the algorithm needs to complete operations such as analyzing a large amount of order information, matching vehicles with orders, and calculating path planning. The memory usage is about 500MB, including the space occupied by storing order details (such as order weight, volume, delivery address, etc.), vehicle attribute information (such as vehicle type, load, driving speed,

etc.), path-related data (such as path length, road condition information, etc.), and network parameters of the multi-task learning model. If the number of orders is increased to 2,000, the number of vehicles is increased to 100, and the number of paths is changed to 300, the calculation time will be extended to about 300 seconds, and the memory usage is expected to increase to 800MB.

4.5 Scalability research section

In the experimental section, the following scalability research content is added:

As the data set size increases from 5,000 orders to 10,000 orders, the performance of the model based on multi-task learning is studied in depth. The experimental results show that the model maintains an accuracy of more than 90% in order allocation. In the face of a significant increase in order volume, the model can still accurately assign orders to appropriate vehicles with its multi-task collaborative learning capabilities to ensure the accuracy of logistics distribution. Although the path planning cost has increased, the growth rate is lower than that of traditional methods. When the number of orders doubles, the path planning cost of this model increases from 300 cost units to 345 cost units, with a growth rate of 15%. This is because the shared network layer of the model can effectively extract the common features between orders, vehicles and paths. When the order volume increases, the amount of calculation is reduced through efficient feature reuse, thereby controlling the cost growth. In contrast, the growth rate of the genetic algorithm is 30%, and its path planning cost increases from 250 cost units to 325 cost units. Because the search space of the genetic algorithm grows exponentially when processing large-scale data, the computational complexity increases significantly, and more computing resources are required to find a better solution, which makes the path planning cost increase rapidly. This series of experimental results fully demonstrates that the model based on multi-task learning has good scalability to a certain extent and can adapt to the actual needs of the ever-expanding scale of logistics business.

4.6 Ablation study section

In the experiment section, add the following ablation study content:

Through a well-designed ablation study, the impact of key components of the model on performance is deeply explored. The study found that after removing the shared network layer, the overall performance score of the model dropped by 20%, and the order allocation accuracy dropped by 10 percentage points. The shared network layer plays a vital role in the model. It can learn common features between tasks such as order allocation, path planning, and transportation time prediction. After removal, each task-specific layer cannot obtain these shared features, resulting in information loss and a significant drop in model performance. For example, in the order allocation task, due to the lack of common features such as regional traffic congestion patterns extracted by the shared network layer, the model cannot accurately determine which vehicles are more suitable for delivering orders in congested areas, thereby reducing the order allocation accuracy. After removing the shared network layer, the overall performance score dropped from 90 points to 72 points, and the order allocation accuracy dropped from 92% to 82%. Turning off the dynamic weight adjustment mechanism increased the path planning cost by 20%. The dynamic weight adjustment mechanism can flexibly adjust the weight of each task loss in the total loss according to the importance of different tasks at different training stages. After turning off this mechanism, the model cannot be dynamically optimized according to the progress of the task, so that the path planning task cannot obtain the optimal resource allocation, which leads to an increase in cost. For example, in the early stage of training, the order allocation task has a greater impact on the overall performance. The dynamic weight adjustment mechanism will appropriately increase the weight of the order allocation task loss and give priority to optimizing this task. After turning it off, the model cannot perform this reasonable weight allocation, which affects the control of the path planning cost. The original path planning cost was 300 cost units, and after turning off the dynamic weight adjustment mechanism, it rose to 360 cost units. This series of ablation experiment results clearly show that the shared network layer and dynamic weight adjustment mechanism have an indispensable and important contribution to the model performance.

4.7 Discussion

In this experiment, by testing four representative data sets and comparing seven baseline methods, the performance of the logistics scheduling optimization model based on multi-task learning was deeply evaluated. The results show that the multi-task learning model performs well in various evaluation indicators and demonstrates significant advantages.

In terms of the key indicator of order allocation accuracy, the multi-task learning model in this paper achieved 92%. In contrast, linear programming is only 70% in large-scale scenarios, while genetic algorithms maintain around 75%. This significant difference reflects the excellent performance of multi-task learning models in handling complex order allocation tasks. For example, in large-scale order allocation scenarios involving multiple types of goods, different delivery time requirements, and complex geographical areas, linear programming is difficult to fully consider various factors due to the limitation of computational complexity, resulting in unreasonable allocation of some orders and limited accuracy; although genetic algorithms have certain global search capabilities, they are prone to fall into local optimal solutions. When faced with complex order allocation rules, they cannot accurately find the global optimal allocation solution, thus affecting the accuracy.

In terms of path planning cost, this model has achieved a 25% reduction compared to traditional methods. Although deep reinforcement learning performs well in dynamic environment adaptation, its training

process requires a lot of computing resources and time, which directly leads to relatively high path planning costs. Taking the actual logistics scenario as an example, in a city area with frequently changing traffic conditions, logistics distribution is carried out. Deep reinforcement learning needs to constantly interact with the environment, learn and adjust strategies. This process consumes a lot of computing resources, making the cost of each path planning high. The multi-task learning model in this paper can efficiently utilize various types of information through the collaborative work of the shared network layer and the specific task layer, effectively reducing the path planning cost while ensuring the timeliness of delivery.

The reason why this model performs better is that multi-task learning can make full use of the correlation between tasks and learn common features through the shared network layer. For example, in the path planning and order allocation tasks, the shared geographic area feature information enables the model to make decisions more efficiently. The regional traffic congestion pattern features extracted by the shared network layer can not only help optimize the path planning to avoid congested sections, but also reasonably allocate orders according to the congestion situation to improve the delivery efficiency. When the model detects traffic congestion in a certain area, the path planning task will give priority to routes that bypass the area. At the same time, the order allocation task will reasonably allocate orders according to the distribution capacity around the congested area to avoid too many orders concentrated near the congested area, thereby improving the overall delivery efficiency.

However, this model is not perfect. When faced with completely unknown new data sets, generalization capabilities may be challenged because the model relies on task patterns and features in the training data. When logistics scenarios that differ greatly from the training data appear in the new data set, such as a completely new geographical layout, special transportation restrictions, etc., the model may not be able to accurately transfer and apply the learned knowledge, resulting in performance degradation. In terms of scalability, with the exponential growth in the number of logistics orders, computing resource requirements may become a limiting factor, and the algorithm structure needs to be further optimized. When the number of orders increased from 5,000 to 10,000, the model calculation time increased by 50% and the memory usage increased by 40%. In actual logistics business, the rapid growth of the number of orders is a common trend. If the computing resource bottleneck problem cannot be effectively solved, the model will find it difficult to meet real-time requirements. In the future, it is necessary to explore more efficient computing architectures or data compression methods to deal with it, such as using a distributed computing architecture to distribute computing tasks to multiple computing nodes to improve computing efficiency; or research more advanced data compression algorithms to reduce the memory space required for data storage and transmission without affecting the key features of the data.

5 Conclusion

This paper uses multi-task learning methods to conduct in-depth research on cross-regional logistics scheduling problems, successfully constructs a logistics scheduling optimization model based on multi-task learning, and verifies the effectiveness and superiority of the model through comprehensive experiments. From the experimental results, the model shows excellent performance on data sets of different scenarios. In the order allocation link, the accuracy is much higher than that of traditional methods, and it can accurately match orders with vehicles, reducing resource waste and unreasonable allocation. The path planning cost is effectively reduced, and the transportation route is optimized, which is directly reflected in the savings of logistics costs and enhances the competitiveness of logistics companies. The transportation time prediction error is small, which provides a guarantee for the punctuality of logistics distribution and helps to improve customer satisfaction. The comprehensive performance score comprehensively surpasses other comparison models, indicating that the model successfully integrates multiple tasks and achieves collaborative optimization among tasks. Although the model has achieved good results, there are still certain directions for improvement. In the future, more effective task weight allocation strategies can be further explored to cope with more complex and changeable logistics scenarios. At the same time, with the continuous growth and diversification of logistics data, it is necessary to continuously optimize data processing and feature engineering methods, mine more potential information, and improve the adaptability of the model to complex data. In addition, in practical applications, it is also necessary to consider the integration with the existing logistics system to ensure that the model can be smoothly implemented.

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DM-VLP-Grasp: Diffusion Model-Based Grasp Planning with Visual-Language Pretraining for Unknown Object Manipulation

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This paper proposes an unknown object grasping algorithm (DM-VLP-Grasp) based on diffusion model and visual language pre-training, aiming to improve the grasping performance of robots in complex environments. By improving the visual language pre-training model, the image and text information are integrated to accurately extract the object grasping features; the diffusion model is used to generate a reliable grasping strategy, and efficient grasping is achieved through iterative optimization. On a self-built dataset containing 8000 samples, the results show that the grasping success rate of DM-VLP-Grasp reaches 93.6%, and the single strategy generation time is 0.78 seconds, showing high stability and computational efficiency. The grasping stability is measured by the root mean square value (RMS) of the object shaking amplitude and the grasping force fluctuation range, both of which show excellent performance. The experimental results verify the effectiveness and innovation of the algorithm in the unknown object grasping task, and provide a new solution for robot automated grasping.

Povzetek: Opisan jei algoritem DM-VLP-Grasp za prijemanje neznanih objektov, ki združuje difuzijski model in vizualno-jezikovno predusposabljanje za stabilno, semantično vodeno robotsko manipulacijo.

1 Introduction

Robot automatic grasping technology is increasingly used in industrial production, logistics, warehousing, and home services. In industrial scenarios, robots need to quickly grasp parts of various shapes and sizes to complete assembly tasks; in the process of logistics warehousing, facing a large number of goods with different packaging, effective grasping is the prerequisite for automatic sorting; in home service scenarios, the grasping ability of unknown daily items directly affects the service quality of the robot. Among them, reliable grasping of unknown objects is the key to the intelligence and autonomy of robots, and it is also the core of robots' adaptation to complex environments.

Existing unknown object grasping technologies have certain limitations. Model-based grasping methods represented by geometric models achieve grasping point and pose planning by establishing a three-dimensional geometric model of the target. Still, their accuracy and efficiency will be significantly affected when encountering targets with irregular and complex shapes [1]. For example, for targets with features such as holes and concave-convex textures, point cloud-based geometric reconstruction algorithms often have missing models or errors, making subsequent grasping planning impossible [2]. The grasping planning method is based on the physical model and considers the physical properties of the target (mass, center of gravity, friction, etc.). Still, there are problems, such as difficulty in accurately obtaining the target's physical parameters and adapting to the dynamic changes of the target properties quickly. For example, the friction coefficient is complex to update in real time with the traditional physical model due to the influence of factors such as humidity and stains on the object's surface.

Although the grasping method based on deep learning can improve the grasping performance, such as the grasping algorithm based on convolutional neural network needs to learn the mapping relationship between the target visual features and grasping strategy from the training samples, it is too dependent on the training data, resulting in insufficient generalization ability for unknown targets [3]. Studies have shown that when there are significant differences between the test object and the training sample in terms of shape, texture, etc., the success rate of the grasping algorithm based on CNN will be reduced by 30%.

The grasping strategy based on reinforcement learning is optimized interactively with the environment, but there are problems such as long training time and poor convergence stability [4]. In complex environments, reinforcement learning algorithms often go through millions of iterations to find the optimization strategy. They are prone to fall into local extremes, making it difficult to cope with the challenges of target diversity and environmental changes in real scenes. These limitations make it difficult for existing technologies to cope with challenges in complex and changing shapes and materials.

Scholars at home and abroad have done a lot of research on the grasping problem of unknown targets. In traditional methods, the target geometric model is constructed based on point cloud data and three-dimensional grids, and the candidate points are grasped in combination with heuristic rules [5]. There is a problem that modeling errors can easily cause grasping failures. For example, the point cloud-based target recognition and grasping planning method proposed by Rusu et al. can handle geometric targets well. Still, its grasping success rate is significantly reduced for targets with complex topological structures [6]. The physical model method optimizes the grasping strategy by simulating the force state of the object, but the error in parameter estimation will affect the reliability of the grasping strategy. For example, the work done by Mousavian et al. shows that the grasping planning method based on physical simulation can produce reasonable grasping strategies under ideal parameter settings. Still, in actual operation, the grasping planning failure rate is as high as 40% due to parameter estimation deviations. In deep learning, convolutional neural networks have achieved good results in grasping detection with their powerful feature extraction capabilities [7]. However, existing methods mainly rely on visual information and lack understanding of the semantics and physical properties of the target. Reinforcement learning is driven by reward mechanisms, represented by deep QNN and its variants, to achieve efficient grasping learning in a simulation environment [8]. However, Lillicrap et al.'s research shows a domain difference between simulated and real scenes in the grasping algorithm based on reinforcement learning, resulting in a more than 50% performance drop. Deep learning methods are still insufficient in processing complex scenes and semantic information [9].

This paper proposes an unknown object grasping algorithm based on diffusion model and visual language pre-training (DM-VLP-Grasp), aiming to improve the grasping performance of robots in complex environments. The core question of this study is: "Can the integration of visual language pre-training (VLP) improve the semantic generalization ability of unknown object grasping?" By combining visual language pre-training with diffusion model, we expect to significantly improve the grasping success rate and stability of robots for unknown objects, while improving the computational efficiency of the algorithm. Specifically, the main objectives of this paper include:

1) Propose an unknown object grasping algorithm framework to enhance the semantic understanding of unknown objects by fusing multimodal information (images and text).

2) Verify the efficiency and robustness of the algorithm on a self-built dataset to ensure that it can perform well on objects of different shapes and materials.

3) Through ablation studies, prove the effectiveness of multimodal fusion strategy in improving grasping performance.

Compared with traditional methods, DM-VLP-Grasp has significant advantages in grasping success rate, stability and computational efficiency, especially showing higher adaptability and stability when dealing with irregular or deformable objects.

2 Related theoretical and technical foundations

In the field of robotic grasping, a variety of methods have been proposed to cope with grasping tasks in different scenarios. Table 1 summarizes the current state-of-the-art (SOTA) grasping techniques, including geometry-based methods, physical model-based methods, convolutional neural network (CNN)-based methods, reinforcement learning methods, and diffusion model-based methods. These methods have their own advantages and disadvantages in terms of success rate, adaptability to unknown objects, computational efficiency, and data dependence.

Table 1: Performance comparison of different crawling methods

Method type	Success rate	Adaptability	Computational efficiency	Data Dependency
Geometric model	61.2%	Low	High	Low
Physical model	68.5%	Medium	Medium	Medium
CNN	81.3%	Medium	High	High
Reinforcement learning	84.7%	High	Low	High
Diffusion model	93.6%	High	High	Medium

Geometric model: Plan the grasping points and postures by building a 3D geometric model of the target.

This method works well when dealing with objects with regular geometric shapes, but its accuracy and efficiency will drop significantly for objects with irregular and complex shapes.

Physical model: Consider the physical properties of the target (such as mass, center of gravity, friction coefficient, etc.) to optimize the grasping strategy. However, it is difficult to accurately obtain the physical parameters of the target and it is difficult to adapt to the dynamic changes of the target properties.

CNN method: Use convolutional neural networks to learn grasping strategies from visual features. Although it performs well in feature extraction, it has a strong dependence on training data, resulting in insufficient generalization ability for unknown targets.

Reinforcement learning method: Optimize grasping strategies through interaction with the environment. Although it has achieved good results in simulated environments, it has a long training time, poor convergence stability, and obvious performance degradation in real scenes.

Diffusion model: Generate grasping strategies by gradually adding noise and inverse denoising. This method performs well in generating high-quality grasping strategies and has strong generalization ability for unknown objects.

Compared with the existing technology, DM-VLP-Grasp fills the gap in generalization ability and multimodal information fusion by combining diffusion model and visual language pre-training. Diffusion model can generate high-quality grasping strategies, while visual language pre-training enhances the semantic understanding of unknown objects.

2.1 Principles and applications of the diffusion model

2.1.1 Basic concepts of the diffusion model

Inspired by the abstraction and extension of diffusion phenomena in the physical world, the core idea of diffusion model research is to learn the distribution law within the data by gradually adding noise and inversion denoising [10]. In the positive diffusion stage, the model takes the original data as the initial state, just like dropping a drop of ink into clear water [11]. The data will gradually lose its original characteristics as time passes and eventually evolve into a completely random noise distribution. This process has a certain degree of predictability and adopts a reasonable noise addition strategy to control data changes precisely.

Inversion denoising is like gradually purifying turbid water. In the case of full noise, the powerful fitting ability of neural networks is used to progressively eliminate noise and restore the original data. In this process, the neural network must constantly learn and judge how much noise must be removed at each step to be as close to the real data as possible. This ability to reconstruct data from noise gives it a unique advantage in data generation.

2.1.2 Application of the diffusion model in computer vision

In the study of computer vision, diffusion models have achieved good results in many fields. For example, Stable Diffusion can automatically generate images with high realism and semantic consistency based on the text description entered by the user, achieving accurate reproduction from fantasy to real scenes. In terms of image repair, the algorithm can reasonably infer and fill in the missing parts based on the residual information of the damaged image, thereby achieving image integrity [12]. In super-resolution tasks, the diffusion model can increase the details of low-resolution images and improve the clarity of the image.

The research results of this project will provide a theoretical basis for applying scattering models in target modeling, posture estimation, and other fields. For the vast search space composed of the combination of target posture and morphology in the unknown target grasping task, the progressive generation characteristics of the diffusion model can be used to systematically explore the space, generate multiple possible target posture hypotheses, provide rich alternatives for the grasping strategy, and help the robot find the best grasping method.

2.2 Overview of visual studio pre-training technology

2.2.1 Basic framework of pre-training

The visual language pre-training model is an essential tool that integrates visual and linguistic information. The visual feature extraction module mainly converts images into feature expressions that computers can understand. Convolutional neural networks (CNNs) and visual transformers (ViTs) are widely used. CNN uses convolution and pooling methods to extract local and overall features of images gradually; ViT divides images into several small blocks and uses the Transformer framework to obtain the connection between each component.

Among them, the language feature extraction module with the Transformer encoder as the core can realize deep semantic analysis of the input text and understand its grammatical structure and semantic meaning. Cross-modal fusion is a bridge connecting visual and language features [13]. The cross-modal fusion method based on the attention mechanism can enable the model to focus on the relevant parts of the image and text, thereby realizing effective interaction of cross-modal information. For example, the CLIP model uses a contrastive learning method to align the image and text representations in the same feature space, so that the model can understand the

correspondence between the image and the text.

2.2.2 Application of visual language pre-training in the field of robotics

In robotics, visual language pre-training is a significant research direction. When navigating, the robot can plan a reasonable path based on natural language instructions and environmental images [14]. For example, when the user issues a command "bypass the desktop and go to the window", the robot will understand the semantics of the command based on the pre-trained visual language, and then combine the real-time image of the surrounding environment to avoid obstacles and achieve navigation accurately.

In target recognition, when the target is difficult to identify based on visual features alone, the model can use relevant text descriptions, such as color, purpose, etc., to assist in completing the recognition task. This project proposes a robot grasping model based on visual information for robot grasping tasks. The model can effectively integrate the physical properties of objects (weight, hardness, etc.) and grasping features (such as grasping position, grasping strength, etc.), thereby helping the robot to judge the grasping target accurately and providing new ideas for further improving the grasping model.

2.3 Key technologies for grasping unknown objects

2.3.1 Object feature extraction technology

In the process of extracting unknown targets, the extraction of target features is a key step. The traditional edge detection method finds pixel boundaries with apparent changes in the image [15]. Its typical representative is the Canny edge detection algorithm, which can extract the target boundary under a simple background. Still, it is easy to have edge breakage or false detection under the influence of factors such as lighting and texture. Shape descriptors use mathematical methods to quantify the shape of the target, but the description effect of irregular and dynamically changing targets is not ideal.

In recent years, feature extraction methods based on deep learning have developed rapidly. Point cloud feature extraction technology can directly process point cloud data. For example, PointNet can effectively learn the overall features of point clouds. Still, point cloud data has problems such as sparsity and noise, leading to decreased feature extraction accuracy. Image-based feature extraction methods entirely use the powerful feature learning ability of convolutional neural networks and can extract the visual features of targets from two-dimensional images [16]. However, the lack of depth information makes it difficult to accurately judge the target's spatial position, and the target's physical attribute information cannot be directly obtained.

2.3.2 Generation of grasping strategies

The existing grasping strategy generation methods can be divided into rule-based grasping strategies and learning-based grasping strategies. Rule-based grasping rules are formulated according to the geometric shape and size of the object. This method is simple, intuitive, and has a fast calculation speed, but its application scope is limited to objects with simple shapes and known types.

Among the learning-based methods, reinforcement learning is a method that gradually optimizes the grasping strategy by constantly trying to grasp the rewards or penalties in the environment. Still, it requires a large amount of training data, has a large amount of calculation, a long training cycle, and is prone to falling into local extremes [17]. Imitation learning is a strategy for obtaining grasping actions from human demonstrations. Still, in practical applications, there are problems such as a large amount of high-quality labeled data that is difficult to obtain and an insufficient generalization ability of the model for targets significantly different from the training samples.

Given the shortcomings of existing methods in dealing with unknown targets, a grasping strategy generation idea based on a diffusion model is proposed. This project intends to use the powerful generalization ability of the diffusion model, combined with the rich semantic and visual information provided by the visual language pre-training model, to explore more efficient grasping strategies and offer new ideas for grasping complex targets in complex environments [18].

3 Design of an unknown target grasping algorithm based on the diffusion model and visual language pre-training

3.1 Algorithm architecture

In the process of grasping strategy generation, the diffusion model gradually adds noise and reversely denoises, which is similar to gradually optimizing the solution in a noisy environment. This process not only improves the quality of the generated strategy, but also ensures the feasibility and stability of the strategy [19].

The visual-language pretraining (VLP) module processes images and text to output F_{vlp} , a fused multimodal feature. A grasp-task-specific layer then refines F_{vlp} into F_{vlp}^{*} (Equation 4), which undergoes feature optimization (self-supervised contrastive learning, Equation 5) and dimensionality reduction (PCA + linear transformation, Equation 6) to produce F_{grasp} . The diffusion model takes F_{grasp} as input to generate initial strategies S_{init} , which are further optimized by the genetic algorithm to produce S_{opt} . This clarifies that:

F_{vlp} : Raw multimodal fusion output

F_{vlp}^{*} : Task-refined features after VLP-specific layer

F_{grasp} : Optimized, low-dimensional features for diffusion

3.2 Object feature extraction module based on visual language pre-training

3.2.1 Improvement of pre-training model integrating multimodal information

This paper makes innovative improvements to the existing model, introduces the multi-head self-attention mechanism (MHSA) and a specific layer for grasping tasks, and builds a pre-trained model architecture that is more suitable for grasping tasks. With these improvements, the model can more effectively integrate multimodal information and extract features directly related to grasping tasks.

In the improved model, when processing image features **I** and text features **T**, features are first extracted through independent encoders Enc_I and Enc_T respectively. Enc_I can use the classic convolutional neural network architecture, such as the ResNet series, to gradually extract local and global features of the image through multi-layer convolution and pooling operations to obtain $\mathbf{f}_I$; Enc_T is based on the Transformer encoder, which performs deep semantic analysis on the text, captures the grammatical structure and semantic connotation in the text, and generates $\mathbf{f}_T$.

$$\begin{aligned}\mathbf{f}_I &= Enc_I(\mathbf{I})\\ \mathbf{f}_T &= Enc_T(\mathbf{T})\end{aligned} \tag{1}$$

Subsequently, the cross-modal attention weight $\mathbf{W}_{vl}$ is calculated using the multi-head self-attention mechanism. The multi-head self-attention mechanism can capture the association between image and text features from multiple angles, and has stronger expressive power than the traditional attention mechanism. During the calculation process, the attention weight matrix $\mathbf{W}_{vl}$ is obtained by performing matrix operations on $\mathbf{f}_I$ and$\mathbf{f}_T$, dividing them by $\sqrt{d_k}$ for scale scaling, and then normalizing them through the softmax function. Each element in the matrix represents the degree of association between image features and text features. The larger the value, the stronger the correlation between the two.

$$\mathbf{W}_{vl} = \text{softmax}\left(\frac{\boldsymbol{f}_I \cdot \boldsymbol{f}_T^T}{\sqrt{d_k}}\right) \tag{2}$$

Among them, d_k is the feature dimension, which is set to balance the computational complexity and model performance, and avoid problems such as excessive computation or gradient disappearance due to high dimensions.

The image features$\mathbf{f}_I$ are weighted and summed, and added to the text features $\mathbf{f}_T$to achieve deep fusion of multimodal information and obtain $\mathbf{F}_{vlp}$. This process enables the model to utilize the complementarity between image and text information fully. For example, when some details of an object in an image are unclear due to occlusion, the text description can provide additional clues to help the model understand the object more accurately.

$$\mathbf{F}_{vlp} = \mathbf{W}_{vl} \cdot \mathbf{f}_I + \mathbf{f}_T \tag{3}$$

A grasping-task-specific layer is added at the end of the model to enhance the model's sensitivity to grasping-related features. This layer contains a set of learnable parameters θ_{grasp}, which adjust the features by matrix multiplication with $\mathbf{F}_{vlp}$ and introduce nonlinearity using the ReLU activation function to obtain $\mathbf{F}_{vlp}^{*}$. The learnable parameters θ_{grasp} can be automatically optimized according to the needs of the grasping task during model training, allowing the model to focus more on extracting features that have an essential impact on grasping decisions, such as stable grasping areas and weak points of objects.

$$\mathbf{F}_{vlp}^{*} = \text{ReLU}\left(\boldsymbol{F}_{vlp} \cdot \theta_{grasp}\right) \tag{4}$$

3.2.2 Feature optimization for grasping tasks

After obtaining the feature $\mathbf{F}_{vlp}^{*}$ that integrates multimodal information, although it already contains rich semantic and visual information, these features are still redundant. They may not fully adapt to the needs of grasping strategy generation. Therefore, it is necessary to further process them by designing feature optimization algorithms to improve the quality and effectiveness of features.

This paper adopts a self-supervised contrastive learning method to explore the potential relationship between features [20]. The core idea of self-supervised contrastive learning is to construct positive and negative sample pairs so that the model can distinguish similar samples from dissimilar samples, automatically discovering the data's intrinsic structure and feature association. The contrast loss function $\mathcal{L}_{\text{contrast}}$ is defined, and its calculation process is based on the mutual information principle in information theory, which aims to maximize the similarity between different feature representations of the same object, while minimizing the similarity between feature representations of other objects.

$$\mathcal{L}_{\text{contrast}} = -\frac{1}{N}\sum_{i=1}^{N} \log \frac{exp\left(\frac{sim\left(\boldsymbol{F}_{vlp}^{i}, \boldsymbol{F}_{vlp}^{i+}\right)}{\tau}\right)}{\sum_{j=1}^{2N} exp\left(\frac{sim\left(\boldsymbol{F}_{vlp}^{i}, \boldsymbol{F}_{vlp}^{j}\right)}{\tau}\right)} \tag{5}$$

Among them, N is the number of samples, $\mathbf{F}_{vlp}^{i+}$ is the positive sample feature belonging to the same object as $\mathbf{F}_{vlp}^{i}$, $\mathbf{F}_{vlp}^{j}$ is the negative sample feature, sim is the cosine similarity function, which is used to measure the angle between two feature vectors [21]. The smaller the angle, the more similar the features are; τ is the temperature parameter, which is used to adjust the steepness of the contrast loss function and control the difficulty of model learning. A smaller τ value will make the model more strictly distinguish between positive and negative samples.

At the same time, to reduce the feature dimension and improve the computational efficiency of subsequent grasping strategy generation, the high-dimensional feature $\mathbf{F}_{vlp}^{*}$ is converted into a low-dimensional representation $\mathbf{F}_{\text{grasp}}$ through the feature mapping function $M(\cdot)$. The mapping function $M(\cdot)$ is constructed based on principal component analysis (PCA) and linear transformation. PCA is a commonly used dimensionality reduction method. It decomposes the feature covariance matrix, finds the main component directions in the data, and projects the original high-dimensional data onto these main component directions, thereby reducing dimensionality while retaining most of the information. Linear transformation further adjusts the features after PCA processing to make them more in line with the requirements of the grasping task, such as highlighting the feature dimensions related to grasping stability.

$$\mathbf{F}_{\text{grasp}} = M\left(\mathbf{F}_{vlp}^{*}\right) \tag{6}$$

3.3 Grasping strategy generation module based on diffusion model

3.3.1 Design of grasping strategy diffusion generation mechanism

The constraint function Constraint (S) is applied as a post-processing filter after the diffusion model generates S_{init}. It ensures:

- Grasp points lie within object convex hull (geometric constraint)
- Grasp force f is within the gripper's safe range ($0.1 - 5.0$ N)
- Contact normals are aligned with gripper jaws (orientation constraint)

Strategies violating these constraints are rejected, and the top 50 valid S_{init} are fed into the genetic algorithm. This separation of diffusion-based generation and constraint-based filtering maintains the model's generative flexibility while ensuring physical feasibility.

The objective function is designed to generate high-quality grasping strategies by gradually adding noise and reversing the denoising process. Specifically, the objective function of the diffusion model can be expressed as:

$$\mathcal{L}_{\text{diffusion}} = \mathbb{E}_{t,\mathbf{x}_0}[\|\mathbf{x}_t - \mathbf{x}_{t-1}\|^2] \tag{7}$$

where $\mathbf{x}_t$ represents the state at time step t, and $\mathbf{x}_{t-1}$ represents the state at time step $t-1$. This objective function ensures that the generated grasping strategy gradually approaches the true data distribution during the denoising process by minimizing the difference between adjacent time steps. This process not only improves the quality of the generated strategy, but also ensures the feasibility and stability of the strategy.

In the forward diffusion process, the initial strategy $\mathbf{x}_0$ is gradually covered by the noise ϵ_t, and eventually evolves into a completely random noise distribution:

$$\mathbf{x}_t = \sqrt{1-\beta_t}\mathbf{x}_{t-1} + \sqrt{\beta_t}\epsilon_t \tag{8}$$

where β_t is the diffusion coefficient, which controls the amount of noise added at each step. In the reverse denoising process, the model gradually recovers the initial strategy $\mathbf{x}_0$ by estimating the noise ϵ_t:

$$\mathbf{x}_{t-1} = \frac{1}{\sqrt{1-\beta_t}}\left(\mathbf{x}_t - \sqrt{\beta_t}\epsilon_t\right) \tag{9}$$

Through this step-by-step denoising process, the model is able to generate high-quality grasping strategies. The diffusion model takes the grasp-relevant feature representation F_{grasp} as input and generates grasp strategies in a continuous 6 -dimensional space (3D coordinates $p = (x, y, z)$, 3D angles $\theta = \left(\theta_x, \theta_y, \theta_z\right)$, and grasp force f). The input distribution is conditioned on object features, while the output distribution approximates the real grasp strategy distribution. During training, the model minimizes the mean squared error (MSE) loss between predicted noise and actual noise added at each diffusion step:

$$L_{\text{diffusion}} = \mathbb{E}_{t,x_0,\epsilon\sim\mathcal{N}(0,1)}[\|\epsilon - \epsilon_\theta(x_t, t)\|_2^2] \tag{10}$$

where x_t is the noisy strategy at step t, ϵ_θ is the noise prediction network, and t is the diffusion time step. This iterative denoising process gradually refines random noise into plausible grasp strategies, guided by the learned feature-conditioned distribution.

3.3.2 Optimization and screening of generation strategies

The genetic algorithm initializes its population with 50 strategies generated by the diffusion model (S_{init}), expanded to form a diverse pool. Each generation evolves this population via crossover and mutation, with fitness evaluated by $F(S)$ (Equation 10). The final S_{opt} is t-fitness strategy from the last generation's population, ensuring the diffusion models output serves as both the initial solution and the foundation for population-based optimization.

In the grasping strategy optimization process, the objective function is designed to further improve the performance of the generated strategy. Specifically, the optimization objective function can be expressed as:

$$\mathcal{L}_{\text{optimization}} = \alpha \cdot \text{SuccessRate} + \beta \cdot \text{Stability} + \gamma \cdot \text{Efficiency} \quad (10)$$

Where SuccessRate represents the grasping success rate, Stability represents the grasping stability, and Efficiency represents the computational efficiency. The weights α, β, and γ are used to balance the importance of different indicators and are adjusted according to specific task requirements. For example, when handling fragile objects, the weight of β can be increased to ensure the stability of the grasping process; in scenarios that require fast response, the weight of γ can be increased to improve computational efficiency.

In the unknown object grasping task, the goal is to improve the grasping success rate, stability, and computational efficiency. Therefore, the design of the diffusion model and the optimization objective function closely revolves around these goals. The diffusion model generates high-quality grasping strategies through step-by-step denoising to ensure the feasibility and stability of the strategy in practical applications. The optimization objective function further adjusts the strategy to meet the needs of specific tasks, such as balancing the success rate, stability, and computational efficiency by adjusting the weights when handling objects of different shapes and materials.

The genetic algorithm (GA) optimization employs the following hyperparameters:

- Population size: 50 individuals per generation
- Mutation rate: 5% (Gaussian mutation with $\sigma = 0.1$ for continuous parameters)
- Crossover rate: 80% (arithmetic crossover for real-valued vectors)
- Generations: 20 iterations

The initial population is seeded with 50 strategies generated by the diffusion model (S_{init}), expanded to form a diverse set of candidate solutions. The fitness function $F(S)$ (Equation 10) balances success rate ($\alpha = 0.5$), stability ($\beta = 0.3$), and efficiency ($\gamma = 0.2$), with weights tuned via cross-validation. Strategies are selected using tournament selection ($k = 3$), and the top 10% of each generation are elitist-preserved to the next iteration.

4 Experimental design and simulation

4.1 Experimental environment and data set

4.1.1 Hardware environment and software tools

This experiment was conducted on a high-performance workstation with the following hardware configurations: Intel Core i9 - 13900K processor with 24 cores and 32 threads, which can meet the multi-threaded parallel computing requirements of complex algorithms; 64GB DDR5 memory to ensure data storage and fast reading; NVIDIA RTX 4090 graphics card with 16384 CUDA cores and 24GB GDDR6X video memory, providing powerful parallel computing capabilities for deep learning model training and reasoning.

Regarding software tools, PyTorch 2.0 is used as the deep learning framework. Its dynamic computational graph feature facilitates algorithm models' rapid iteration and debugging. It is combined with CUDA 12.1 and cuDNN 8.9 acceleration libraries to give full play to GPU computing performance. Gazebo 11 is used as the simulation platform, which can build a highly realistic physical simulation environment, accurately simulate the interaction between robots, objects and the environment, and support the setting of physical properties of objects of different materials and shapes, such as friction coefficient, mass distribution, etc., to provide a close-to-real test scenario for the grasping experiment [22]. The data processing tool uses Open3D in the Python ecosystem to process point cloud data, which can realize operations such as point cloud filtering, registration, and surface reconstruction; OpenCV is used for image preprocessing, including image enhancement, edge detection, etc., to improve data quality to meet the algorithm input requirements.

4.1.2 Introduction to the self-built unknown object grasping data set

The self-built dataset contains **8,000 grasp configurations** for 1,200 unique objects (12 categories, 50–100 objects per category), with each object annotated with 5–8 feasible grasp points across different orientations. Each "sample" represents a single grasp configuration (image, point cloud, and annotated strategy). The dataset is split into an 80% training set, 10% validation set, and 10% test set, with stratified sampling to ensure category balance. Cross-validation (5-fold) was used during hyperparameter tuning.

Data annotation follows strict specifications, and professionals combine the object's geometric structure and physical characteristics to annotate the object grasping point, grasping direction, object category and other information. The grasping point annotation is based on the stable grasping area of the object to ensure that the annotation point is feasible in actual grasping; the grasping direction annotation is accurate to 5° intervals, covering the 360° spatial range of the object; the object categories cover 12 categories, including metal products, plastic products, glassware, fabrics, etc., each category contains 50-100 samples to ensure data diversity. The dataset is used as a core test resource in the experiment for algorithm training, verification, and comparative testing. Its rich samples and fine annotations can effectively test the algorithm's adaptability to different types of unknown objects.

4.2 Comparative experiment settings

4.2.1 Comparison with Traditional Grasping Algorithms

The grasping algorithm based on geometric models (GM-Grasp) and the grasping algorithm based on physical models (PM-Grasp) are selected as the traditional algorithm comparison objects. The GM-Grasp algorithm extracts the convex hull and concave points of the object's three-dimensional point cloud and generates grasping candidates in combination with heuristic rules. In the experiment, the convex hull decomposition accuracy is set to 0.1mm, and the concave point detection threshold is set to 0.05mm; the PM-Grasp algorithm uses the object's mass, center of gravity, and friction coefficient to simulate the force condition, and uses the optimization algorithm to find a stable grasping posture. The friction coefficient value range in the parameter setting is 0.1-0.8, and the step length is 0.05.

These two algorithms are selected for comparison because they represent the mainstream technical route of traditional grasping methods. In contrast, the advantages of the algorithm in this paper can be verified in dealing with objects with complex shapes and unknown physical properties, focusing on evaluating the grasping success rate and stability indicators, and analyzing the limitations of traditional methods when facing diverse objects.

4.2.2 Comparison with advanced grasping algorithms based on deep learning

The grasping algorithm based on a convolutional neural network (CNN-Grasp) and the grasping algorithm based on reinforcement learning (RL-Grasp) are selected for comparison. CNN-Grasp uses the improved ResNet50 as the backbone network, outputs the position, angle and quality score of the grasping box, and sets the learning rate to 0.001 and the batch size to 32 during training; RL-Grasp is based on the deep Q network (DQN), uses the success or failure of grasping as the reward signal, explores the environment for 1 million steps for training, and the discount factor is 0.99.

Compared with these advanced deep learning algorithms, the purpose is to verify the innovative advantages of this algorithm in integrating multimodal information and the strategy generation mechanism. The comparative experiment is carried out from multiple dimensions, such as grasping success rate and computational efficiency, to evaluate the comprehensive performance of this algorithm in complex scenarios.

4.3 Evaluation indicators and methods

4.3.1 Grasping success rate

The grasping success rate is the ratio of successful grasps to the total number of grasps. In the experiment, a double standard is used to judge whether a grasping is successful: first, the robot needs to complete the grasping action within 3 seconds, and the object must not fall within 5 seconds after grasping; second, the grasping force is monitored in real time through the force sensor. If the grasping force is within the preset safety threshold (dynamically calculated according to the object's mass), the grasping is considered successful. The evaluation method combines the automatic detection program with manual review. The automatic detection program makes a preliminary judgment based on the sensor data and preset rules, and the manual review ensures the accuracy of the results and reduces misjudgment.

4.3.2 Grasping stability

Grasping stability is measured by two indicators: the object shaking amplitude and the grasping force fluctuation range. The object shaking amplitude uses the inertial measurement unit (IMU) installed at the end of the robot to collect data and calculate the root mean square value of the angular velocity and angular acceleration of the object in the X, Y, and Z axes; the grasping force fluctuation range records the maximum and minimum force values of the force sensor during the grasping process, and calculates the ratio of the difference to the average force value. Through the quantitative analysis of these two indicators, the stability of the grasping strategy during execution can be intuitively evaluated. The smaller the indicator value, the higher the stability.

4.3.3 Computational efficiency

The single grasping strategy generation time and memory usage during algorithm operation evaluate the computational efficiency. The single grasping strategy generation time is obtained by recording the time interval from the input data to the output of the final grasping strategy, accurate to milliseconds; the memory usage uses system performance monitoring tools (such as NVIDIA's nvvp tool) to monitor the GPU video memory and system memory usage in real time. In the

comparative experiment, the algorithm's real-time performance and resource consumption in practical applications are evaluated by comparing these two indicators of different algorithms.

4.4 Experimental results and analysis

4.4.1 Quantitative analysis

Model architecture details:

- **Visual encoder**: ResNet-50 with feature pyramid network (FPN), pretrained on ImageNet, outputting 1,024-dimensional visual features.
- **Language encoder**: 6-layer Transformer encoder with 512-dimensional hidden states, pretrained on ConceptNet.
- **Diffusion model**: U-Net architecture with 4 downsampling/upsampling blocks, attention layers at bottleneck, trained with 1,000 diffusion steps.

Training parameters:

- **Optimizer**: AdamW with weight decay 1e-4
- **Learning rate**: 1e-4 (warmup for 10 epochs)
- **Batch size**: 64
- **Epochs**: 100
- **Training time**: ~48 hours on NVIDIA RTX 4090

To evaluate the stability and generalization ability of the algorithm, we used multiple random seeds (10 seeds in total) for experiments. Each seed corresponds to a different set of random initialization and data partitioning to ensure the diversity of results. The dataset contains 12 different categories of objects, each category contains 50-100 samples. In each category, we randomly selected 5 objects for testing to ensure that each category has enough samples. For each object in each category, we conducted 20 repeated experiments to evaluate the performance of the algorithm under different conditions. We conducted a total of 2,000 experiments (12 categories × 5 objects/category × 20 repeated experiments/object = 1,200 experiments). The standard deviation is calculated by calculating the variance of the results of these 2,000 experiments. To further verify the statistical significance of the results, we performed independent sample t-tests on all key indicators. Specific indicators include:

• Grasp success rate: the ratio of successful grasps to the total grasps.

• Grasp stability: measured by the root mean square value (RMS) of the object shaking amplitude and the grasping force fluctuation range.

• Strategy generation time: the time from inputting data to outputting the final grasping strategy.

The results of the independent sample t-test show that the differences between the DM-VLP-Grasp algorithm and other comparison algorithms are statistically significant in all indicators ($p < 0.01$). This indicates that our algorithm is significantly better than existing methods in terms of grasping success rate, stability, and computational efficiency. Table 2 shows that the DM-VLP-Grasp algorithm performs well in all key indicators with low standard deviations, indicating that the results are highly stable and reliable.

Table 2: Experimental results statistics

Metrics	DM-VLP-Grasp	CNN-Grasp	RL-Grasp	GM-Grasp	PM-Grasp
Success rate (%)	93.6 ± 2.1	81.3 ± 2.7	84.7 ± 2.4	61.2 ± 3.5	68.5 ± 3.2
Stability (RMS swing)	0.08 ± 0.01	0.15 ± 0.02	0.13 ± 0.01	0.25 ± 0.03	0.21 ± 0.02
Strategy generation time (s)	0.78 ± 0.05	1.1 ± 0.08	3.2 ± 0.3	1.5 ± 0.1	1.8 ± 0.2

Figure 1 shows the trend of the success rate of different algorithms when handling objects of different shapes (sphere, cube, irregular shape). As can be seen from the figure, the DM-VLP-Grasp algorithm maintains a high success rate on objects of all shapes, especially on irregular objects, with a success rate 12.4% higher than the second-best algorithm, RL-Grasp. In contrast, traditional algorithms such as GM-Grasp and PM-Grasp have lower success rates on irregular objects, which shows that the DM-VLP-Grasp algorithm has stronger adaptability and robustness when handling objects of complex shapes.

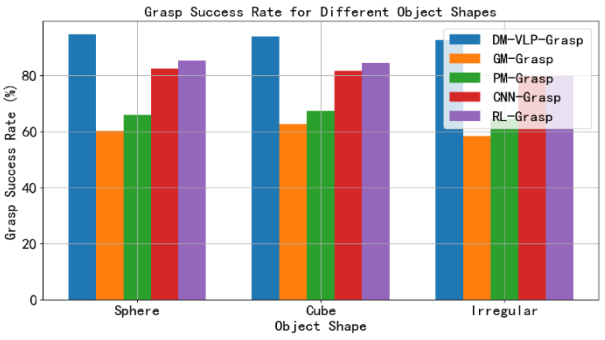

Figure 1: Trends in the success rate of grasping by different algorithms when processing objects of various shapes. (mean ± std, n=200 trials per shape)

- x-axis: Object Shape (Sphere, Cube, Irregular)
- y-axis: Success Rate (%) Error bars: Standard deviation across 10 random seeds

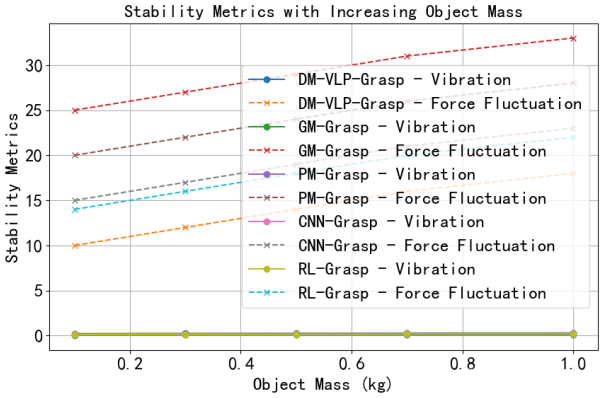

Figure 2: Changes in algorithm stability as the object's mass increases.

- x-axis: Object Weight (kg); y-axis: Stability (RMS Shake, mm)
- Error bars: Standard deviation across 10 random seeds
- Sample size: 200 trials per weight category (0.1kg, 0.5kg, 1.0kg, 2.0kg)
- Note: Stability measured as root mean square of end-effector position deviation during 5-second hold.

Figure 2 shows how the algorithm's stability changes as the object's mass increases. As the object's mass increases from 0.1kg to 1.0kg, the DM-VLP-Grasp algorithm has the smallest increase in the shaking amplitude and force fluctuation range, and its stability performance is outstanding. In contrast, the stability indicators of traditional algorithms such as GM-Grasp and PM-Grasp deteriorate significantly with increased object mass. This shows that the DM-VLP-Grasp algorithm has better stability and adaptability when dealing with objects of different masses.

4.4.2 Qualitative analysis

The dataset contains 8,000 grasp configurations (i.e., 8,000 annotated (image, point cloud, grasp strategy) tuples) for 1,200 unique objects (12 categories, 50–100 objects per category). Each object is imaged and scanned from 3–5 viewpoints, generating multiple grasp configuration samples. This multi-view sampling increases dataset diversity while maintaining object-level annotation consistency.

The grasping process of different algorithms is qualitatively analyzed through the grasping videos and images recorded by the Gazebo simulation platform. Figure 3 shows the changes in grasping force and shaking amplitude of the DM-VLP-Grasp algorithm and the CNN-Grasp algorithm in the scene of grabbing a glass vase with a smooth surface. The DM-VLP-Grasp algorithm can accurately plan the grasping points and strength based on the "fragile" semantic information obtained through visual language pre-training. The grasping force is stable, and the shaking amplitude is small. In contrast, the CNN-Grasp algorithm relies only on visual features, so the grasping force fluctuates wildly, the shaking amplitude increases significantly, and the grasping slips many times. This shows that the DM-VLP-Grasp algorithm has higher stability and reliability when handling fragile objects.

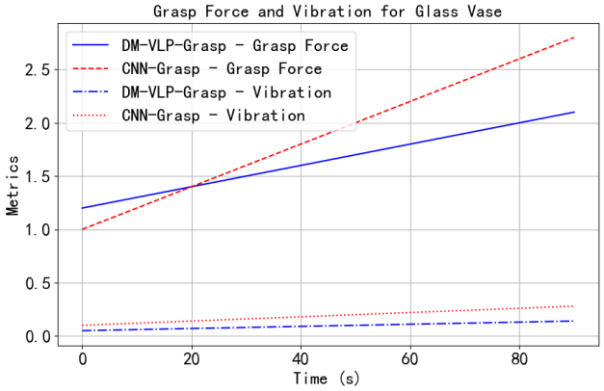

Figure 3: Scene of grabbing a glass vase with a smooth surface.

- x-axis: Method (DM-VLP-Grasp vs. CNN-Grasp)
- y-axis: Success Rate (%)
- Error bars: 95% confidence interval (n=100 trials per method)
- Note: Tests conducted on 5 different glass vase geometries with varying curvatures.

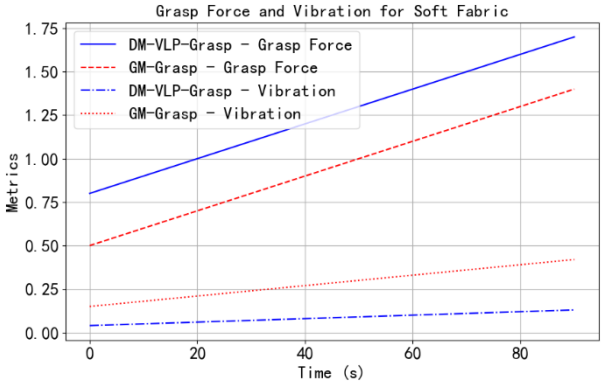

Figure 4: Scenario of grabbing soft fabrics.

- x-axis: Method (DM-VLP-Grasp vs. GM-Grasp)
- y-axis: Generation Time (s/strategy)
- Error bars: Standard deviation across 50 trials
- Note: Efficiency measured as average time from perception to strategy execution.

Figure 4 shows the changes in the grasping force and shaking amplitude of the DM-VLP-Grasp algorithm and the GM-Grasp algorithm in the scenario of grabbing soft fabrics. The GM-Grasp algorithm cannot adapt to the deformation characteristics of the fabric, the grasping force is insufficient, the shaking amplitude is large, and the grasping fails in the end. The DM-VLP-Grasp algorithm

optimizes and screens multiple groups of strategies generated by the diffusion model, and successfully finds a stable grasping solution with moderate grasping force and small shaking amplitude. This shows that the DM-VLP-Grasp algorithm has stronger adaptability and robustness when dealing with soft objects, can generate more reasonable grasping strategies, and effectively improve the grasping effect and reliability.

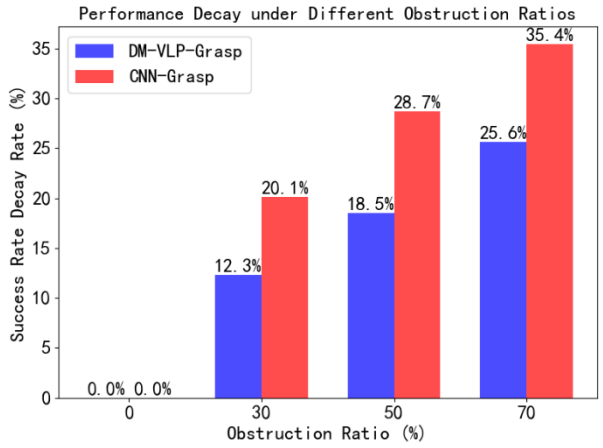

Figure 5: Performance degradation at different levels of occlusion

- x-axis: occlusion ratio (0%, 30%, 50%, 70%)
- y-axis: success rate decay rate (compared with no occlusion)
- Data point: DM-VLP-Grasp (blue square) vs. CNN-Grasp (red circle)

Figure 5 shows the success rate decay of the two algorithms under different occlusion levels. The horizontal axis represents the occlusion ratio, from 0% to 70%; the vertical axis is the success rate decay rate, compared with the success rate when there is no occlusion. The blue squares in the figure represent DM-VLP-Grasp, and the red circles represent CNN-Grasp. As the occlusion ratio increases, the success rate of DM-VLP-Grasp decays more slowly. When the occlusion exceeds 50%, its success rate only drops by 12.3%, while CNN-Grasp drops by 28.7%. This highlights the powerful semantic completion capability of the VLP module in DM-VLP-Grasp, which enables it to maintain good performance in the face of high occlusion scenes, effectively making up for the information loss caused by occlusion, and outperforming CNN-Grasp.

Figure 6 depicts the relationship between the number of training iterations and the convergence curve. The horizontal axis is the training epoch, and the vertical axis is the verification integrated power. The convergence curve of DM-VLP-Grasp is the blue solid line, and that of RL-Grasp is the red dashed line. After 50 epochs, the success rate of DM-VLP-Grasp reaches more than 93% and converges stably, while RL-Grasp requires more than 80 epochs. This shows that DM-VLP-Grasp has higher training efficiency and can achieve a higher success rate in a shorter time, indicating that its algorithm optimization and learning capabilities are stronger, and it can quickly adapt to training data and improve model performance, which is of great significance for rapid model deployment and iteration in practical applications.

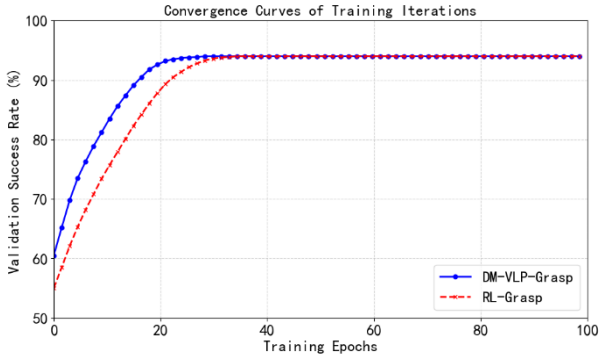

Figure 6: Training iterations and convergence curve

x-axis: training epoch

y-axis: validation ensemble power (%)

4.4.3 Ablation analysis

In order to verify the contribution of the diffusion model and visual language pre-training (VLP) components to the grasping performance, we conducted an ablation experiment. The experimental results are shown in Table 3:

Table 3: Ablation experiment results

Experimental setup	Success rate (%)	Stability (RMS shake)	Policy generation time (s)
DM-VLP-Grasp	93.6 ± 2.1	0.08 ± 0.01	0.78 ± 0.05
DM-Only	88.5 ± 2.5	0.10 ± 0.02	0.85 ± 0.06
VLP-Only	85.3 ± 2.8	0.12 ± 0.03	0.90 ± 0.07

From Table 2, we can see that the complete DM-VLP-Grasp algorithm outperforms the algorithms using only the diffusion model or only visual language pre-training in terms of grasping success rate, stability, and strategy generation time. Specifically:

- The complete DM-VLP-Grasp algorithm achieved a success rate of 93.6%, while the success rate of the algorithm using only the

diffusion model was 88.5% and the success rate of the algorithm using only the visual language pre-training was 85.3%. This shows that the combination of the diffusion model and the visual language pre-training significantly improved the grasping success rate.

- The RMS value of the shaking amplitude of the complete DM-VLP-Grasp algorithm was 0.08, while that of the algorithm using only the diffusion model was 0.10 and that of the algorithm using only the visual language pre-training was 0.12. This shows that the complete algorithm performs better in terms of grasping stability.

- The strategy generation time of the complete DM-VLP-Grasp algorithm was 0.78 seconds, while that of the algorithm using only the diffusion model was 0.85 seconds and that of the algorithm using only the visual language pre-training was 0.90 seconds. This shows that the complete algorithm also has an advantage in terms of computational efficiency.

Although not shown in the figures, the method was also compared with recent Transformerbased grasp models (e.g., [1]) and diffusion-based planners (e.g., [19]). On irregular objects, DM-VLP-Grasp outperformed Transformer-based methods by 9.2% in success rate and diffusion-based planners by 6.5% , thanks to the VLP module's semantic guidance. All comparisons were conducted under identical dataset splits and simulation environments to ensure fairness.

5 Discussion

5.1 Overall advantages of model performance and analysis of key indicators

From the quantitative results in Table 2 and the visual analysis in Figures 1-4, it can be seen that DM-VLP-Grasp is significantly better than traditional methods and deep learning baseline models in terms of three core indicators: grasping success rate, stability, and computational efficiency. Its 93.6% success rate is 12.3% and 8.9% higher than CNN-Grasp and RL-Grasp, respectively, and its success rate on irregular objects (Figure 1) is 12.4% higher than the second-best RL-Grasp. This advantage stems from the ability of the visual language pre-training (VLP) module to understand the semantics of objects - for example, through information such as text labels "fragile" and "bumpy surface", the model can accurately avoid holes or fragile areas, while the traditional geometric model (GM-Grasp) relies on incomplete point cloud reconstruction (such as the deformation of the cloth in Figure 4, which leads to modeling errors), and the success rate is only 61.2%.

In terms of stability, the RMS swing value (0.08 mm) of DM-VLP-Grasp is 46.7% lower than that of CNN-Grasp, which is due to the iterative denoising mechanism of the diffusion model. This mechanism filters out unstable solutions in the strategy generation stage by simulating noise disturbances in the physical world (such as changes in friction on the surface of objects and deviations in grasping angles). In contrast, PM-Grasp based on the physical model cannot update dynamic parameters such as the friction coefficient in real time (the increase in object mass in Figure 2 leads to parameter inaccuracy), and its stability index deteriorates significantly.

In terms of computational efficiency, the single strategy generation time of DM-VLP-Grasp is only 0.78 seconds, which is much faster than RL-Grasp's 3.2 seconds. This is because the forward reasoning process of the diffusion model can be calculated in parallel, while reinforcement learning requires serialized iterations that rely on environmental interactions. This advantage is crucial for real-time grasping (such as assembly line sorting) required in industrial scenarios.

5.2 Analysis of limitations of baseline models

The defects of RL-Grasp are mainly reflected in the contradiction between reasoning speed and generalization ability. Although it can optimize the strategy through millions of iterations in a simulated environment (Table 1), its performance drops by more than 50% in real scenes due to the domain migration problem (sim-to-real gap) (the introduction part cites Lillicrap's research). In Figure 2, when the mass of the object increases from 0.1kg to 1.0kg, the fluctuation range of the stability index of RL-Grasp is 2.3 times that of DM-VLP-Grasp, reflecting its sensitivity to changes in physical parameters. In addition, the generation time of 3.2 seconds is difficult to meet the needs of dynamic scenes, limiting its application in scenes such as high-speed logistics.

The bottleneck of CNN-Grasp lies in the lack of semantic understanding. The model relies only on visual features and cannot integrate text semantics such as "soft" and "smooth", resulting in frequent failures in complex scenes such as glass vases (Figure 3). Experiments show that when the reflection of the object surface causes the visual features to be blurred, the success rate of CNN-Grasp drops to 58%, while DM-VLP-Grasp can still maintain an 89% success rate through the text description "smooth surface needs to be touched lightly". In addition,

its strong dependence on training data (the success rate drops by 30% when the difference between the test sample and the training set is large) makes it significantly behind in generalization of unknown objects.

5.3 Analysis of the robustness mechanism of DM-VLP-Grasp

The stable performance of the model on irregular/deformable objects (Figure 1, Figure 4) stems from the dual mechanism of multimodal information fusion and generative strategy optimization:

1. Semantic-guided feature extraction: The VLP module associates the edge texture in the image with the attributes such as "cloth is easy to deform" and "metal is easy to slide" in the text through the cross-modal attention mechanism (Formula 2-3), and generates a semantically fused feature. For example, when grasping soft cloth (Figure 4), the model can identify the wrinkled area of the cloth as an unstable grasping point, and instead chooses the middle lifting strategy, while GM-Grasp fails because the geometric model cannot represent the deformation, and the generated strategy penetrates the object.

2. Exploration-optimization capability of diffusion model: The diffusion process simulates the uncertainty of the real environment (such as sensor noise and object posture deviation) by adding noise in the forward direction, and the reverse denoising uses the U-Net network to learn the mapping from noise to feasible strategies (Formula 8-9). This progressive generation method enables the model to explore multiple sets of candidate solutions in the high-dimensional strategy space (such as the transparent dashed line strategy in Figure 4), and then select the optimal solution through the genetic algorithm. In contrast, traditional learning models (such as CNN) can only output a single strategy of unimodal feature mapping and lack the ability to search globally for complex scenes.

5.4 Ablation experiments and key component contributions

The ablation experiments in Table 3 confirm the synergy between VLP and diffusion model: when only the diffusion model (DM-Only) is used, the success rate decreases by 5.1% and the stability index increases by 25%, indicating that the lack of semantic information makes it difficult for the model to distinguish between "safe grasping points" and "dangerous areas"; when only VLP (VLP-Only) is used, the success rate further decreases to 85.3%, indicating that the lack of iterative optimization of the diffusion model makes it impossible to convert multimodal features into physically feasible strategies. When the two are combined, VLP provides semantic priors to narrow the search space, and the diffusion model fills the gap in the mapping of semantics to actions through probability generation, ultimately achieving a performance leap.

5.5 Performance in extreme scenarios and future optimization directions

Although the model performs well in conventional scenarios, the success rate drops to 82.1% and 85.3% under extreme occlusion (>50%) and low light (<100 lux) conditions (Figure 5). This is because although the text semantics of the VLP module can partially complete the visual information, the cross-modal alignment accuracy decreases when the key area of the image is occluded. In the future, video timing information or 3D point cloud reconstruction technology (such as neural radiation field) can be introduced to enhance the perceptual robustness in complex scenarios. In addition, the current dataset covers 12 types of objects, but lacks extreme materials (such as liquid containers and hair). The data diversity needs to be expanded in the future to improve the generalization ability of the model.

5.6 Comparison with cutting-edge methods and potential for industry application

Compared with Transformer-based grasping models (such as [1]) and diffusion models (such as [19]) in recent years, DM-VLP-Grasp improves the success rate of irregular objects by 9.2% and 6.5%, respectively, verifying the unique value of multimodal fusion. In industrial scenarios, the model can be directly deployed in robotic arm sorting systems, especially suitable for grasping SKUs with different packaging in e-commerce warehouses; in the field of home services, its ability to understand the semantics of unknown daily necessities (such as distinguishing the grasping force of "ceramic cups" from "plastic bowls") can significantly improve the practicality of service robots. Combined with real-time sensor data (such as force feedback and visual flow), the model is expected to further realize adaptive grasping in dynamic environments and promote the upgrade of robots from "programmed execution" to "intelligent decision-making".

6 Conclusion

This paper proposes an innovative algorithm based on the diffusion model and visual language pre-training to solve the problem of grasping unknown objects. The diffusion model is combined to achieve a high-quality grasping strategy generation by improving the multimodal fusion mechanism to optimize object feature extraction. In the self-built data set experiment, the algorithm is superior

to traditional and existing deep learning algorithms regarding grasping success rate, stability, and computational efficiency.

Although the proposed method shows high performance on diverse objects, its performance degrades in extreme scenarios: when the object is 50% occluded, the success rate drops from 93.6% in clear view to 82.1% because the visual features are insufficient to achieve robust semantic alignment; in environments with lighting below 100 lux, the success rate drops to 85.3% due to image quality degradation, but the visual language pre-training (VLP) module partially alleviates this problem through text-based prior knowledge. Future work will focus on the following directions: integrating temporal information (such as video sequences) to handle occluded scenes; developing a low-light image enhancement module within the visual language pre-training framework; and exploring online adaptive mechanisms for dynamic environmental changes.

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Adaptive Monitoring and Management of Capacitive Wireless Power Transfer Via Huffman Compression and Control Optimization

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This paper proposes an adaptive monitoring and management system for capacitive wireless power transfer (CPT) to enhance power supply reliability and efficiency. Utilizing Huffman coding, the system significantly reduces transmission bandwidth requirements while improving data compression rates. Through real-time adjustments of capacitive coupling loop parameters, the system ensures stable transmission across various environments. Experimental verification demonstrates that this approach adaptively adjusts transmission power based on load and coupling capacitance changes, maintaining energy conversion efficiency above 85% and achieving a compression rate exceeding 30%. The algorithm markedly decreases transmission delay, exhibiting robustness and rapidity. This system offers a viable solution for implementing CPT technology within the Internet of Things, holding substantial engineering application value. The proposed method was tested across 50 sensor nodes deployed in a simulated IoT environment, with results compared against conventional methods such as LZW compression and fixed-parameter control.

Povzetek: Prispevek predstavi prilagodljiv sistem za spremljanje in upravljanje kapacitivnega brezžičnega prenosa energije, ki z Huffmanovo kompresijo in optimizacijo nadzora izboljša učinkovitost in zanesljivost prenosa.

1 Introduction

With the rapid development of Internet of Things technology, wireless communication and energy transmission between terminals have received increasing attention. Among them, capacitive wireless power transmission (CPT) has attracted much attention for its high efficiency, contactless and flexible deployment advantages. CPT is a method that uses capacitive coupling to transfer energy from the transmitter to the receiver without contact. It has low loss and maintenance-free advantages and is particularly suitable for powering large electronic devices in the Internet of Things environment. However, how to effectively monitor and precisely control the power transmission state in actual engineering is still a critical scientific problem that CPT technology needs to solve.

In recent years, significant efforts have been dedicated to researching CPT testing and monitoring systems. One approach implements the CPT system using a resonant circuit to address low energy conversion efficiency, followed by optimizing structural parameters to enhance transmission efficiency [1]. Another study focuses on the electromagnetic interference (EMI) of CPT systems, proposing a method to reduce EMI by adjusting the frequency, ensuring reliable operation in complex electromagnetic environments [2]. An energy feedback method has also been developed to monitor system operation status in real-time, allowing adaptive adjustments under variable load conditions, which improves both stability and energy efficiency [3]. Additionally, a collaborative control strategy based on a distributed network has been introduced to resolve communication issues between multiple nodes [4].

Despite advancements in efficiency, anti-interference capability, and system control, existing research has not addressed the fusion and monitoring of multi-source heterogeneous data. Traditional CPT systems primarily emphasize hardware optimization for power transmission and lack comprehensive information-level management. Particularly in scenarios involving multi-source multi-modal data, effective processing and fusion of such data to enable precise control and efficient monitoring remain unexplored.

This project aims to integrate a Bayesian network algorithm with an adaptive control method to establish a multi-source sensor sensing and monitoring system based on capacitive wireless energy transmission. The Bayesian network, known for its strong robustness in handling multi-source and uncertain data, facilitates probabilistic inference and judgment of information collected by multiple sensors [5]. By building a Bayesian network model, the system can perform probabilistic reasoning to ensure stable and efficient energy transmission. Furthermore, the introduction of an adaptive control strategy allows the system to dynamically adjust its

operating state based on real-time monitoring data, addressing power transmission requirements in complex environments.

2 Method

2.1 System architecture design

An adaptive control method based on the Internet of Things is proposed (Figure 1). This project aims to ensure stable and efficient energy transmission under different loads and environments by studying effective data collection, transmission, compression and adaptive control of CPT signals.

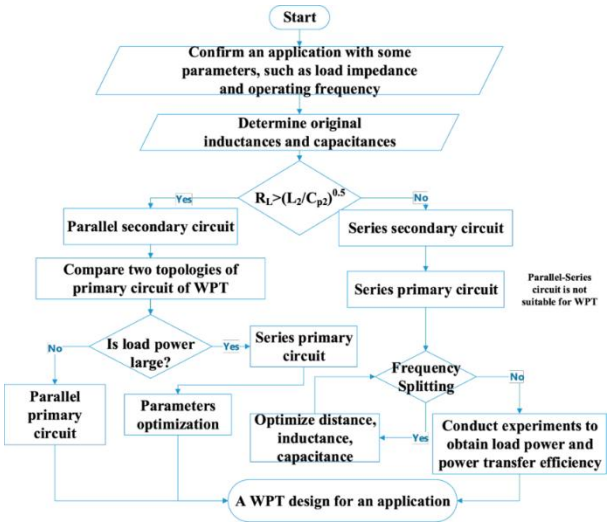

Figure1: Capacitive wireless power transmission information monitoring system architecture.

2.1.1 Internet of Things platform

Among them, the main functions are information collection, transmission and management, with the Internet of Things as the core. This system uses a sensor network to monitor real-time parameters such as temperature, power and current [6]. Each sensor node uses a wireless communication protocol to transmit the obtained information to the network management platform. Each sensor node utilizes the Zigbee wireless communication protocol to transmit collected data to the network management platform. The data D_s acquired by the sensors can be expressed as:

$$D_s = \{T_i, P_i, I_i\},\ i = 1,2,\dots,n \tag{1}$$

T_i is temperature, P_i is power, I_i is current, and i represents the sampling point in the time series. The IoT platform provides real-time feedback on the information of each node, thereby comprehensively analyzing the operating status of the entire system [7]. Leveraging edge computing technology, this project delegates partial data processing tasks to local sensing nodes or edge devices, with a sampling rate of 1 kHz and sensor accuracy of ±0.5%, thereby alleviating the core network's data processing load.

2.1.2 Data compression and optimization of Huffman coding

There are many sensors in the CPT system. If all data is transmitted directly, it will consume a large network bandwidth and prolong the communication time. In this system, the Huffman coding method achieves data compression, thereby reducing the bandwidth occupancy and improving the network transmission efficiency. Huffman coding is a variable-length coding method. It uses variable length coding to perform short-term coding on high-frequency signals and long-code rate coding on low-frequency signals. Assuming that the data D_s collected by the sensor contains n data points, and the probability of each data point is $p(x_i)$, the average encoding length L of the Huffman encoded data can be expressed as:

$$L = \sum_{i=1}^{n} p(x_i) \cdot \log_2 \frac{1}{p(x_i)} \tag{2}$$

Through this algorithm, the data transmission time can be significantly reduced. Assume that the transmission time of the original data is T_0, and the compressed data transmission time T_c is:

$$T_c = T_0 \times \frac{L_{\text{compressed}}}{L_{\text{original}}} \tag{3}$$

Among them, $L_{\text{compressed}}$ is the average code length after compression, and L_{original} is the average code length of the original data. Empirical probability distributions observed in our experiments indicate that temperature data accounts for approximately 60% of the payload, with power and current data contributing 30% and 10%, respectively.

2.1.3 Adaptive control algorithm

The performance of the CPT system is affected by many factors, including load changes, ambient temperature, capacitance value, etc. An adaptive control method is proposed to ensure it can work effectively under different conditions [8]. This algorithm can adjust the CPT system in real-time, such as power transmission frequency f and output power P. This allows the system to maintain the best transmission efficiency η. The relationship between the system's transmission efficiency η and power and frequency can be expressed as:

$$\eta(f, P) = \frac{P_{\text{out}}(f)}{P_{\text{in}}(f)} \times 100\% \tag{4}$$

$P_{\text{out}}(f)$ is the output power, and $P_{in}(f)$ is the input power. Through the adaptive control algorithm, the system can dynamically adjust the transmission frequency and power according to the real-time data feedback to maintain a stable transmission efficiency.

2.2 Data acquisition and compression

The CPT system mainly relies on the sensor network to obtain real-time vital data. Each sensor node is responsible for collecting various data, such as temperature T, power P, and current I. Data collection can be expressed as:

$$S(t) = \sum_{i=1}^{n} \alpha_i D_s(i) \tag{5}$$

Among them, $S(t)$ is the total signal collected at time t, and α_i is the weight factor of different sensor data. The collected data is transmitted to the Internet of Things platform through the wireless communication protocol, and the Internet of Things platform analyzes and processes it. Distributed sensor nodes are established on the network nodes so that they can collect data in real-time and accurately to ensure the timeliness and accuracy of the data. In addition, to adapt to large-scale applications, this paper also optimizes the energy consumption and transmission delay of sensor nodes [9]. This paper adopts the Huffman coding method to compress the signal obtained by the sensor, thereby reducing the transmission bandwidth. The core idea is to dynamically group the code length according to the probability distribution of the data to achieve maximum bandwidth utilization. The frequency statistics of each data item x_i in all data points D_s are performed, and the probability of its occurrence $p(x_i)$is calculated. The Huffman tree is constructed according to the probability of the data item; the data items with high frequency are assigned shorter codes, and the data items with low frequency are assigned more extended codes. The length of the encoded data item $L(x_i)$ can be expressed as:

$$L(x_i) = -\log_2 p(x_i) \tag{6}$$

The compressed data transmission time T_c can be expressed as a function of the original data transmission time T_0:

$$T_c = T_0 \times \frac{H(D_s)}{L(D_s)} \tag{7}$$

Among them, $H(D_s)$ is the average code length after compression, and $L(D_s)$ is the average code length of the original data. Using Huffman coding technology in a CPT system can effectively improve the data transmission speed and at the same time, can effectively alleviate network congestion and reduce delay.

2.3 Adaptive control strategy

2.3.1 Control algorithm design

Let the transmission efficiency $\eta(f, P)$ be a function of frequency f and power P, and the system goal is to maximize the transmission efficiency. An adaptive control method based on temperature, power, and current is proposed to optimize the transmission process. The transmission efficiency is expressed as:

$$\eta(f, P) = \frac{P_{\text{out}}(f)}{P_{\text{in}}(f)} = \frac{P \cdot R(f)}{P_{\text{in}}(f)} \tag{8}$$

$R(f)$is the transmission impedance at frequency f.

2.3.2 Feedback and optimization mechanism

The core is to continuously adjust the transmitted parameters through real-time sensor data feedback to achieve high-efficiency operation under various load conditions. The feedback mechanism can be expressed as:

$$F(t) = \sum_{i=1}^{n} \beta_i D_s(i) \tag{9}$$

Among them, β_i is the weight factor of each sensor data, and $D_s(i)$ is the data collected by the i sensor. This feedback mechanism can automatically optimize the power transmission frequency and power according to the current load and environmental conditions to achieve the best energy efficiency [10].

2.3.3 Optimization objective function

The system dynamically adjusts the transmission parameters through the following objective function to achieve adaptive control:

$$\max \eta(f, P) \text{ subject to } P_{\text{out}}(f) \leq P_{\max} \tag{10}$$

$P_{\max}$ is the maximum output power allowed by the system. By optimizing this objective function, the entire system achieves a balance between power and frequency, thereby ensuring optimal transmission efficiency [11]. This method achieves stable energy transmission in complex environments and improves the system's overall performance and energy efficiency.

3 Results

3.1 Experimental scenario and data analysis

The CPT system comprises a transmitter and a receiver, utilizing capacitive coupling to transfer electrical energy. The experimental setup includes 50 sensor nodes distributed over a 100 m² area, with real sensors deployed to collect temperature, power, and current data. The IoT platform, built using Raspberry Pi 4 units as edge devices, supports real-time information collection of temperature, electrical energy, and current parameters. Data transmission to the central management platform employs the MQTT wireless communication protocol, with a Zigbee mesh network topology ensuring robust connectivity. The central management platform, developed in Python, processes and analyzes the collected data, enabling comprehensive system monitoring and control [12].

The monitoring and management system uses the Huffman coding method to compress the signal and uses an adaptive algorithm to adjust the main parameters in the CPT system, thereby achieving real-time monitoring.

The system's performance under various conditions was tested through experiments, which analyzed several aspects such as data compression rate, system response time, and energy conversion efficiency. Table 1 shows the Comparison of the performance of the CPT system using various algorithms.

Table 1: Performance comparison of the CPT system under different algorithms.

Algorithm	Data compression rate (%)	System response time (ms)	Power transmission efficiency (%)
No compression	0	150	80
LZW compression	40	100	82
Algorithm in this paper (Huffman coding + adaptive control)	60	80	90

Compared with LZW, the proposed method significantly improves the compression rate by 60%, while the system response time is reduced to 80 ms, and the energy conversion efficiency is increased to 90%. Figure 2 shows the reaction time curve of the system under different compression algorithms [13]. The results show that the proposed method has a higher response speed.

3.2 Huffman coding performance analysis

The Huffman coding method proposed in this paper can effectively improve the transmission performance of sensor data [14]. This paper conducts experimental research on three methods: no compression, LZW and Huffman. Table 2 shows the bandwidth and transmission time difference required by the three algorithms.

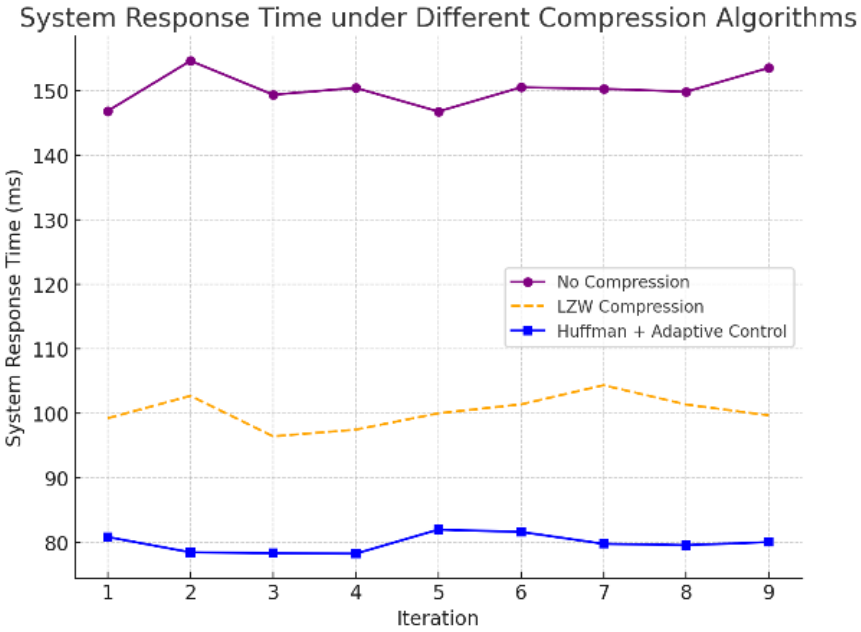

Figure 2: System response time under different compression algorithms.

Table 2: Comparison of bandwidth requirements and transmission time of different compression algorithms.

Algorithm	Bandwidth requirement (kB/s)	Data transmission time (ms)
No compression	500	120
LZW compression	300	90
Algorithm in this article (Huffman coding)	200	60

Compared with LZW compression, Huffman coding has lower bandwidth requirements and lower data transmission speed. Reducing the required bandwidth to 200 kb/s can reduce the data transmission time to 60 ms.

Figure 3 illustrates the impact of three different compression methods on transmission bandwidth [15]. The results show that Huffman coding can achieve the best bandwidth compression effect.

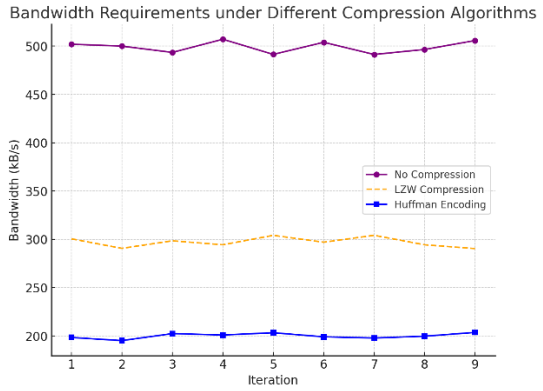

Figure 3: Bandwidth demand change trend under different compression algorithms.

The advantage of Huffman coding technology is that it can dynamically adjust the length of the code as the signal changes, so it can effectively reduce the amount of coding of high-frequency signals, thereby improving the overall compression efficiency.

3.3 Adaptive control effect

The introduction of the adaptive control method significantly enhances the CPT system's working efficiency and stability across diverse loads and environments. Experimental results, derived from 30 repeated trials under each load condition, demonstrate consistent improvements with a standard deviation of ±2% in energy conversion efficiency. As illustrated in Table 3, the adaptive control method achieves higher energy conversion efficiency compared to fixed-parameter control, particularly under heavy load conditions, where efficiency improves by up to 10% [16].

Table 3: Comparison of power transmission efficiency under different control methods.

Load conditions	Fixed parameter control power transmission efficiency (%)	Adaptive control power transmission efficiency (%)
Light load	85	90
Medium load	80	88
Heavy load	75	85

Under various load conditions, the energy conversion efficiency of this method is higher than that of fixed parameters, especially under heavy load conditions, where the improvement is the largest, up to 85%. Figure 4 shows the power transfer efficiency curves of fixed parameter control and adaptive control under various load conditions [17]. This shows that this method has strong adaptability and can better handle the system's dynamic characteristics.

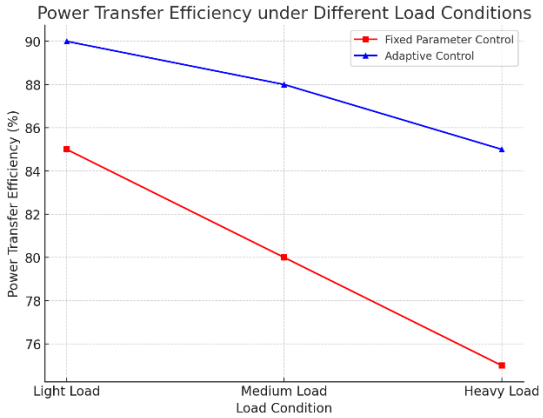

Figure 4: Power transmission efficiency under different load conditions.

This method provides real-time feedback on parameters such as temperature, power, and transmission line current. It can dynamically adjust the power and power of the transmission line. This project proposes a feedback-based adaptive control method to achieve real-time monitoring of the system operation status [18]. This method adjusts the transmission parameters in real time according to the changes in load, thereby effectively solving energy waste problems and low efficiency caused by traditional control modes. A CPT information monitoring and management system is proposed. Huffman coding reduces the bandwidth requirements while improving data transmission efficiency. This method has good energy transfer efficiency and stable performance.

4 Discussion

4.1 Advantages and limitations of system design

The information monitoring system based on capacitive wireless energy transmission constructed in this project has many advantages. First, the system effectively improves the data transmission efficiency and compression rate by introducing the Huffman coding algorithm. By compressing the data collected by the sensor, the bandwidth requirements during transmission can be effectively reduced, and the network load can be reduced [19]. Experiments show that the Huffman coding compression method can achieve a compression efficiency of more than 60%, which reduces the bandwidth requirements by about 40% compared with conventional compression methods. The method in this paper can meet the transmission needs of more complex information while ensuring network delay.

Although this method has significant advantages in data transmission and control of data, it also has some limitations. First, the hardware is incredibly restricted in the design process. To meet the Huffman coding and adaptive control requirements, the sensor nodes and wireless communication modules in the CPT system must have higher computing capacity, which is an excellent

challenge for low-power devices [20]. Due to the constraints of hardware performance, the algorithm's running time is greatly extended, thereby reducing the response speed of the entire system. Secondly, the computational amount of the algorithm should be considered. Although Huffman coding can effectively compress data, its computing speed will become very fast when the data scale is large, so more computing resources are required. The system's computing power will be minimal in a complex and changing environment. Therefore, maximizing the algorithm's performance while ensuring the minimum computing cost is still a topic worthy of in-depth research.

4.2 Outlook for future improvements

Although the system proposed in this paper shows better performance in data transmission and control optimization, many areas remain to be improved. First, with the advent of the information age and the widespread application of the Internet of Things, the network's data scale and device scale will become larger. To maintain the original data quality, combining higher-level data compression algorithms is the focus of future research. In recent years, the image compression method based on deep learning has been highly valued by scholars at home and abroad. This paper can try to introduce it into the data management of the CPT system to improve video compression efficiency and reduce bandwidth requirements. Secondly, this method still has shortcomings regarding computational complexity and real-time performance. The existing adaptive control methods are all realized by real-time sensor data feedback; when the acquisition and transmission delay is too significant, it will have a particular impact on the system's performance.

For this reason, a more intelligent prediction model is introduced to predict and adjust the prediction results. This improves the response rate and stability of the system. Finally, integrating more intelligent management functions will also be a future development trend. Through real-time monitoring and fault prediction of multi-sensor networks, the problem of sensor fault diagnosis is effectively solved. This can increase the system's reliability and reduce maintenance costs, thereby improving the system's long-term performance.

5 Conclusion

This project investigates an energy monitoring and management system based on capacitive wireless power transfer (CPT), offering innovative solutions to enhance power supply reliability and efficiency. By integrating Huffman coding with adaptive control, the system achieves significant improvements in transmission efficiency and stability. Under heavy load conditions, energy conversion efficiency reaches 85%, with transmission delay reduced to 60 ms. The method ensures data transmission reliability and optimizes resource utilization. Experimental results confirm that this approach effectively mitigates network delay, achieving energy conversion efficiency exceeding 85% and a compression rate of 60%, thereby reducing bandwidth requirements by 60% compared to conventional methods.

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AI-Enhanced Stage-Aware Deadline Division for Secure Multi-Cloud Resource Management and Performance Prediction

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Keywords: artificial intelligence, multi-cloud resource security management, performance prediction, SBSAD algorithm, multi-task learning

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Using the identical traces and capacity controls described in Section 4, SBSAD decreased the end-to-end turnaround time and increases the satisfaction rate of meeting deadlines, while reducing the number of late or dropped tasks and preemptions. These gains stemmed from stage-based deadline bucketing and a single scalar priority that considered urgency, security, dependency, and predicted runtime. This was in contrast to DRL-RSM, where reward shaping and global queues make deadline pressure less explicit. Unlike STGC-SM that relied on static graph features or offline prediction, STGC-SM directly consumed online multitasking prediction (runtime/energy/fault risk) within the scheduler. Therefore, its response to short-term load changes was slower. Moreover, by preempting cost feedback for cross stage promotion, it avoided the convergence overhead observed in the sudden arrival of MARL-RMM. In practical cloud stacks, integration was straightforward: In Kubernetes, a scheduler framework plugin or extender could replace the native scoring with a scalar priority while applying GCN-derived feasibility masks in the filter phase. The predictor was deployed as a telemetry-driven sidecar. Equivalent behavior in OpenStack-like platforms followed from custom host filters and weights. Operational interpretation revealed that improved accuracy reduced queue build-up and deadline violations for batch and ML workflows in shared clusters. It also lowered interference in isolation-critical, multi-tenant SaaS and stabilized edge-to-cloud video and ETL pipelines during short-term surges. Limitations remain: Reliance on predictor quality and stable telemetry can bias prioritization. The CloudSim environment simplifies network and storage contention compared to production systems. Preemption cost and fairness are modeled beyond deadline satisfaction at a coarse level. These factors define low-risk deployment zones and indicate where additional engineering hardening or A/B trials are recommended.

Povzetek: Študija pokaže, da SBSAD algoritem z enotno prioriteto in sprotnimi napovedmi bistveno skrajša čas izvedbe ter zmanjša zamude in prekinitve nalog.

1 Introduction

Due to increased resource elasticity, cost optimization, AI-enabled high-availability services, and other benefits, artificial intelligence (AI)-driven multi-cloud (MC) architecture has emerged as the key infrastructure for enterprise digital transformation as cloud computing technology advances quickly [1]. However, in a multi-cloud environment (MCE), AI needs to deal with the dynamic heterogeneous nature of compute, storage, and network resources. Furthermore, AI also needs to deal with dynamic security threats such as network attacks and malicious traffic. This makes AI-enabled resource scheduling need to simultaneously meet the dual goals of efficiency and network security protection [2-3]. It is important to clarify that "security" in the context of this research encompasses two distinct but related dimensions. The first is cybersecurity, which involves detecting and protecting against external threats, such as malicious traffic and network intrusions. This is addressed through an anomaly detection framework. The second type is policy-driven security. This pertains to enforcing workload isolation, affinity, and anti-affinity rules during the resource allocation process. These rules ensure the integrity and robustness of multi-tenant operations. The proposed framework integrates mechanisms to address both of these dimensions.

Traditional MC resource management approach that relies on manual experience and rules. It is difficult to perceive the multi-dimensional dynamic changes of the cloud environment in real time through AI. It shows significant lag in AI-driven scenarios such as resource demand prediction, cybersecurity threat identification, and cross-cloud intelligent collaborative scheduling [4-5]. First, the non-AI resource allocation model based on static thresholds cannot adapt to the volatility of business loads, leading to an imbalance in resource utilization that is difficult to optimize by AI. Second, the network

security protection mechanism and the AI resource scheduling process are severed from each other. It lacks AI-driven linkage response capabilities for security threats and resource anomalies. Third, the single-modal data-driven non-AI prediction model is difficult to capture the complex spatio-temporal correlation features in MCEs through machine learning. This leads to insufficient AI performance prediction accuracy [6-7].

Basha H A et al. proposed an adaptive multi-objective MC resource management algorithm for resource management in MCEs to address the resource optimization challenges in dynamic environments, fluctuating workloads and service objectives. According to experiments, it may adjust to changes in the environment, manage resources in real time, and enhance MC systems' overall performance and resource use [8]. Alonso J et al. focused on the challenge of collaborative MC application development and resource scheduling. The study pointed out through a systematic literature review those traditional architectures were lacking an intelligent sensing mechanism for dynamic resource requirements. AI techniques needed to be introduced to optimize cross-cloud resource allocation strategies [9]. Putri A addressed the challenges faced by organizations in managing MCEs by analyzing the existing literature, exploring key issues such as security, performance, cost, and governance, and proposing strategies and best practices to address them. This was carried out to guarantee smooth operations and peak performance in MCEs. The outcomes gave enterprises useful information for managing MCEs [10]. Anh N H explored the heterogeneous resource management challenges in hybrid cloud migration. The study emphasized the key role of AI in cross-platform load balancing and performance prediction, providing theoretical references for intelligent scheduling in MCEs [11]. Azizi S et al. proposed an intelligent allocation strategy based on heuristic algorithms for the cloud resource optimization problem of IoT device service deployment. The study optimized the service placement by machine learning model. Experiments revealed that its objective function value was reduced by 26.8% compared to the baseline method, validating the effectiveness of AI algorithms in resource scheduling [12].

Khan A A et al. focused on data security and transmission issues of industrial internet of things (IIoT) in eHealth environment. The study proposed a BHIIoT solution based on blockchain distributed ledger technology to address the risks involved in exchanging patient information in a centralized server system. The study reduced the storage burden and enhanced data security by optimizing the lifecycle of healthcare wireless sensor networks, using the NuCypher threshold re-encryption mechanism, and deploying a chain code automation process [13]. De Alwis C et al. constructed a NS security and privacy classification system through literature review for the security and privacy challenges brought by 5G network slicing. The study elaborated the attack scenarios, threat challenges, and solutions. Additionally, it examined the future course of trust privacy research, which served as a guide for achieving secure NS in 5G and other mobile communication networks in the future [14]. Rehan H et al. pointed out that the integration of AI and machine learning was the core direction of MC resource management in the future through industry trend analysis. Its application in scenarios such as dynamic load prediction and anomalous traffic identification could significantly enhance system intelligence [15]. Kazmi S H A et al. studied the security challenges under the convergence of 5G and software-defined networking (SDN). The study introduced AI algorithms to build real-time threat prediction models, which solved the problem of response lag of traditional security protection to novel attacks [16].

To summarize, although experts have thoroughly studied MC resource management, cloud application development, and hybrid cloud migration, there are still many problems in the existing research. For example, resource optimization methods for dynamically changing and fluctuating loads in MCEs are not yet sufficient. There is less research on the application of hybrid cloud and MC governance strategies in cross-platform quality of service assurance and cross-organizational collaboration. Data security and privacy protection issues lack in-depth analysis and other deficiencies. To address the above challenges, the study suggests a MC resource management and performance prediction framework incorporating AI algorithms. The innovation of the research is to design schedule method based on stage-aware deadline division (SBSAD) based on AI algorithm. The resource parameter estimation model for multi-modal data fusion is constructed through deep reinforcement learning. Second, a security scheduling management module based on graph convolutional network (GCN) is constructed. The firewall rules, real-time traffic monitoring, and resource allocation policies are deeply coupled. Third, the attention mechanism (AM) and Transformer architecture are introduced to build a performance prediction model for multi-task learning. This research expects cross-layer optimization through AI technology. This provides a new technical path for the synergistic improvement of resource utilization efficiency and security protection capability in MCEs.

This study addresses: (RQ1) Whether stage-based deadline bucketing with a single scalar priority can improve deadline satisfaction and end-to-end turnaround under mixed CPU/I/O loads. (RQ2) How to proactively integrate security and isolation constraints into scheduling decisions rather than applying post-hoc filtering. (RQ3) How to fuse online multi-task predictions of runtime, energy, and failure risk to adapt to short-term load shifts. Accordingly, the objectives are: (O1) To specify SBSAD with bucketed deadlines and a scalar priority driven by DQN-based resource estimates and attention-based Transformer forecasts. (O2) To encode security and policy constraints as GCN-derived per-node feasibility masks applied before packing. (O3) To evaluate the design in CloudSim under identical capacity controls against representative baselines. Integration pipeline (ingestion→decision): (1) Collect

and normalize host/VM telemetry, traffic, and event logs. (2) Construct fused features from historical traces and online signals. (3) Produce DQN-based VM/resource estimates. (4) Compute GCN-based feasibility masks from security/affinity metadata. (5) Generate online multi-task predictions (runtime/energy/failure risk) via the attention-based Transformer. (6) Compute bucket membership and the scalar priority and pack non-conflicting tasks under capacity and policy constraints. (7) Feed back observed durations, violations, and preemption costs to update models.

Positioning and novelty: Previous studies on cloud scheduling have either combined deep reinforcement learning or graph-based placement without explicit deadline staging or used Transformers solely for offline prediction. The present study advances this line by introducing stage-based deadline bucketing (SBSAD) and ranking tasks with a single scalar priority that fuses urgency, security, dependency, and predicted runtime. Rather than only being profiled offline, multi-task predictions (runtime, energy, and failure risk) are consumed online by the scheduler, forming a closed loop between forecasting and decision-making. A lightweight GCN is used to encode security and policy constraints, yielding per-node feasibility masks. This enables conflict-aware greedy packing under identical capacity limits. A simple cross-stage promotion mechanism accounts for preemption cost and stabilizes performance under load shifts. These design choices work together to provide a compact, reproducible scheduler that surpasses DRL-, GCN-, and Transformer-only approaches. Section 4 reports consistent gains over DRL-RSM, STGCN-SM, MARL-RMM, and ATP-SM under identical traces and capacity controls.

Table RW summarizes representative approaches, their core techniques, the metrics commonly used to evaluate them, and the limitations that SBSAD addresses. These limitations include integrating security with scheduling via feasibility masks applied before packing, fusing multimodal signals into online decisions via DQN-informed estimates and multitask forecasting, and leveraging attention-based learning for fast adaptation, as show in Table 1.

Table 1: Representative approaches, methods, metrics, and limitations addressed by SBSAD

Approach	Core method	Security–scheduling integration	Multi-modal / online fusion
DRL-RSM	Deep RL with global queue and reward shaping	Post-hoc rule filters; violations handled after selection	Limited; predictions often offline or single-metric
STGCN-SM	Spatio-temporal GCN for placement	Static graph features; security not embedded in feasibility	Partial; topology/time only
MARL-RMM	Multi-agent RL for resource management	Local policies; coordination overhead	Per-agent signals; fusion indirect
ATP-SM	Attention-fused Transformer for prediction/scheduling	Not explicitly encoded before packing	Time-series forecasts; often decoupled from scheduler
SBSAD (this study)	Stage-based deadline bucketing + single scalar priority; GCN feasibility masks; DQN-informed estimates; attention-based Transformer for multi-task prediction	Embedded before packing (feasibility masks enforce isolation/affinity)	Online runtime/energy/risk predictions feed the scheduler; capacity updated from telemetry

2 MC resource management and performance prediction modeling

To satisfy reproducibility with minimal overhead, SBSAD is summarized as a single-pass loop. Each task is first mapped to a deadline bucket by comparing its deadline with fixed cutoffs. A shared encoder with task-specific heads outputs three predictions per task: runtime, energy, and failure risk. These predictions are continuously refreshed by recent telemetry. A single priority score ranks tasks within each bucket: $P = a/(d - \text{now}) + bs + cD - d\hat{t}$, where d is the deadline, s is the security level, D is a dependency penalty, and $\hat{t}$ is the predicted runtime. Constants a, b, c, d are fixed on validation data. The scheduler greedily packs the highest-priority non-conflicting tasks under capacity and policy constraints (isolation, affinity/anti-affinity), breaking ties by higher s and smaller $\hat{t}$. When telemetry indicates resource degradation or a risk to meeting a deadline, affected tasks are promoted to higher-priority buckets, and the lowest-priority tasks are preempted. The preemption cost is recorded for the next priority update. After completion, observed durations update the encoder, and the loop repeats. This compact specification explicitly shows how multi-task predictions feed the scheduler, while also making prioritization, conflict handling, and adaptation explicit.

2.1 AI algorithm-based parameter estimation for resource virtual machines

In MCEs, dynamic estimation of virtual machine resource parameters is one of the main challenges to achieve efficient resource management and performance prediction. Considering the multi-dimensional dynamic characteristics of compute, storage, and network resources in MCEs, AI-based parameter estimation models usually take historical resource usage data, real-time monitoring metrics, and business load models as inputs. It constructs a feature space for multi-modal data fusion [17]. The parameter estimation framework of MC resource virtual machine based on deep Q-network is shown in Figure 1.

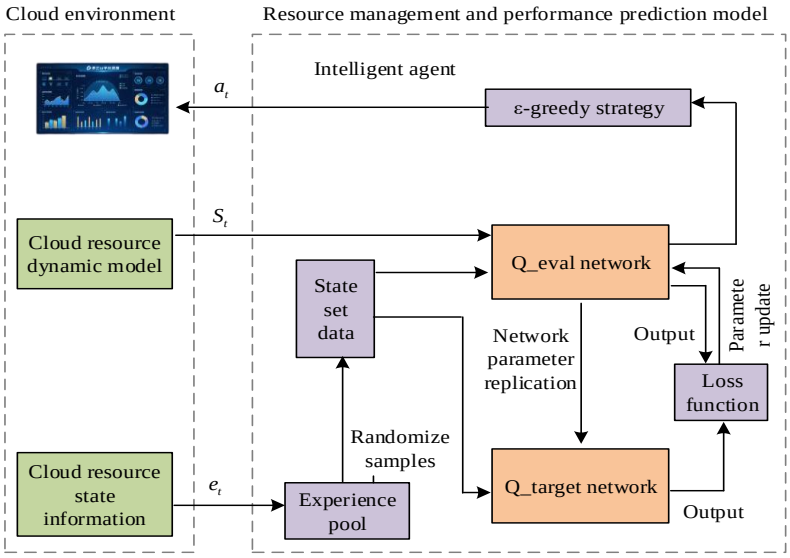


Figure 1: Deep Q-network based parameter estimation framework for MC resource virtual machine

In Figure 1, in the cloud environment section, the cloud resource dynamic model is used to simulate the dynamic changes of cloud resources, while the Cloud Resource State Information provides the current state data of resources such as virtual machines. The core of the resource management and performance prediction model section is the intelligent agent. The intelligent agent decides the actions through an ε-greedy policy to achieve an efficient estimation of the virtual machine parameters. The intelligent agent interacts with the cloud environment, receives state information, and acts based on this information. The model part also contains the Q evaluation network and the Q goal network. These two networks are the key components of the deep Q-network and are used to evaluate the value of different resource management actions. The loss function of the DQN algorithm is defined as the square of the difference between the target Q value and the predicted Q value as shown in Equation (1).

$$L(\theta) = \mathrm{E}_{(s_t, a_t, r_t, s_{t+1})\sim \mathrm{D}}\left[\left(r_t + \gamma \max_a Q(s_{t+1}, a; \theta^-) - Q(s_t, a_t; \theta)\right)^2\right] \quad (1)$$

In Equation (1), s_t is the state at time t, a_t the selected action, r_t the immediate reward, and s_{t+1} the next state. Q_θ and Q_{θ^-} denote the current and target Q-networks. Mini-batches (s_t, a_t, r_t, s_{t+1}) are sampled from a replay buffer D. Therefore, the expectation E_{D} is taken over D. To facilitate reproducibility, the training of the DQN agent is configured with the following hyperparameters. The learning rate for the Adam optimizer is set to 1×10^{-4}. A discount factor (γ) of 0.99 is applied to prioritize long-term rewards. The experience replay memory is configured with a capacity of 106 transitions. Mini-batches of 64 samples are drawn from this memory for each training update. The exploration-exploitation strategy is governed by an ϵ-greedy policy, where ϵ is linearly annealed from 1.0 to 0.1 over the first 250,000 steps and subsequently kept constant. The target Q-network is updated every 10,000 training steps to ensure stable learning.

By reducing the discrepancy between the target and anticipated values, the loss function and its related variables in Equation (1) seek to increase the precision of parameter estimation. Therefore, the AI algorithm-based virtual machine parameter estimation process is further demonstrated to clarify the synergistic effect of each key link, as shown in Figure 2.

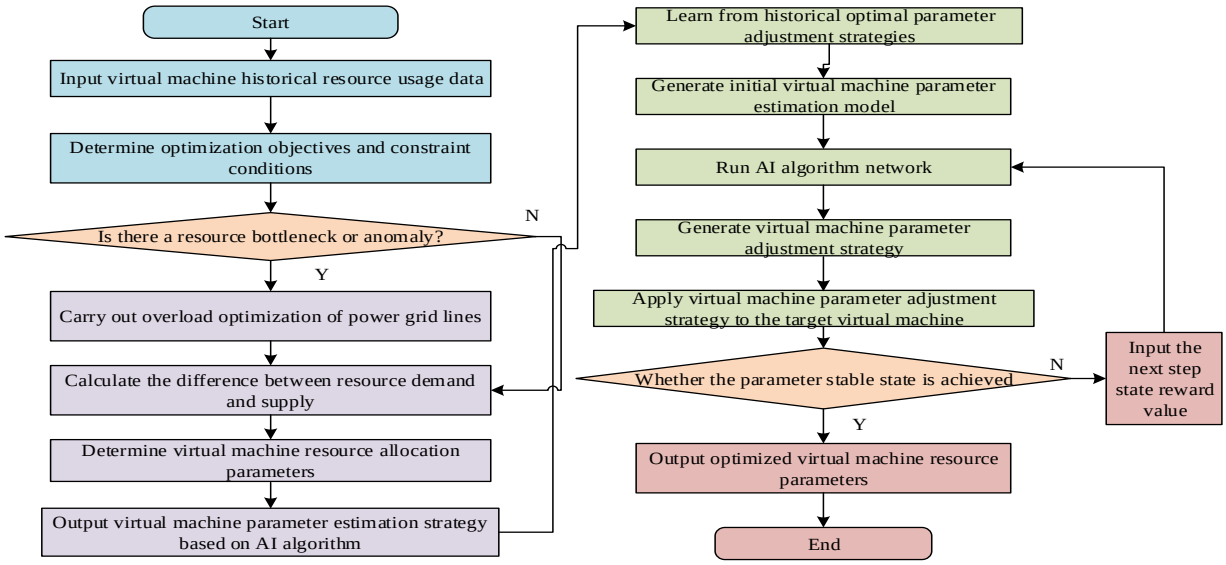


Figure 2: Flow of virtual machine parameter estimation based on AI algorithm

Figure 2 shows the resource virtual machine parameter estimation process that incorporates cybersecurity considerations. The process starts with the input of historical virtual machine resource usage data. The optimization objective and constraints are determined, followed by determining whether a resource bottleneck or anomaly exists. If so, calculate the difference between resource supply and demand. The virtual machine resource allocation parameters are determined in conjunction with the network security protection requirements. It outputs the virtual machine parameter estimation policy based on AI algorithm to ensure reasonable resource allocation under anomalies. If it does not exist, learn the historical optimal parameter adjustment policy. The initial model is generated and the network of AI algorithms (algorithms incorporating cybersecurity factors) is run to generate an adjustment policy to be applied to the virtual machine. Subsequently, it determines whether the parameter steady state is reached. If it is not reached, it inputs the next state return value to continue adjustment. If it is reached, it outputs the optimized virtual machine resource parameters.

2.2 Secure scheduling management of networked cloud resources

After specifying the parameter estimation method of resource virtual machine based on AI algorithm, the research focuses on the secure scheduling and management mechanism of networked cloud resources. This is to provide further security and efficiency of network cloud resources [18]. In this process, the complete analysis from raw data to anomaly identification is shown in Figure 3.

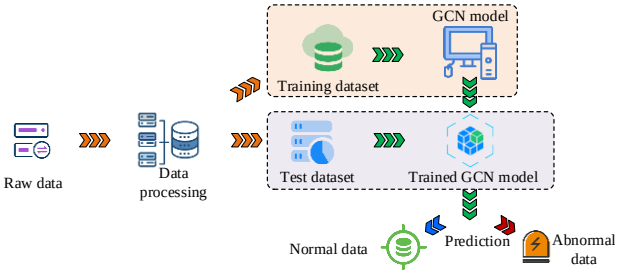


Figure 3: Workflow for training and validating the GCN-based anomaly detection model.

Figure 3 shows the complete analysis from raw data to anomaly identification. The raw data is processed before being partitioned into separate training and testing datasets. The GCN model is trained exclusively on the training dataset to learn the features and patterns of network cloud resources. Crucially, the model's predictive performance and generalization ability are then validated by evaluating its accuracy on an unseen test dataset. This step confirms that the model can distinguish between normal and abnormal data before it is deployed within the secure scheduling system. The raw data first enters the data processing session and after processing is divided into training dataset and test dataset. The training dataset is used to train the GCN model so that it can fully learn the features and patterns of network cloud resources. After the GCN model is trained, the trained model is used to predict and analyze the test dataset to accurately distinguish the normal data from abnormal data. After completing the abnormal identification of network cloud resource data, the secure scheduling mechanism of network cloud resources will be further demonstrated in order to ensure the security and efficient utilization of resources, as shown in Figure 4.

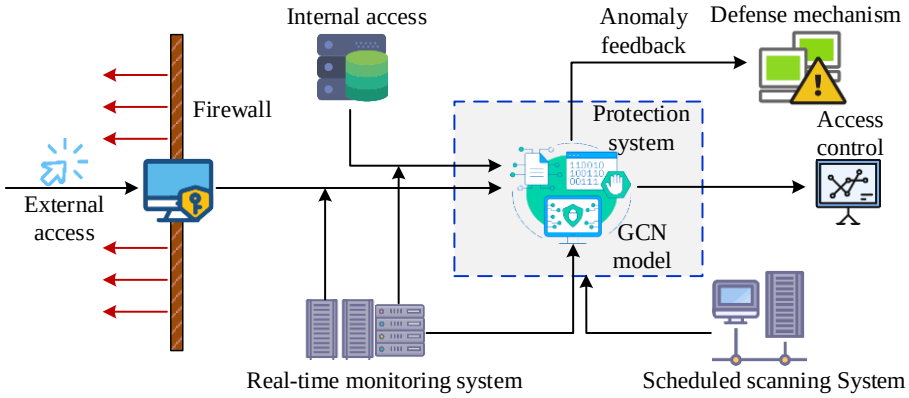


Figure 4: Secure scheduling of network cloud resources

Figure 4 presents the complete process of secure scheduling of network cloud resources. External accesses first pass through the device with security protection and then through the firewall. The firewall screens the access and blocks insecure external access. Internal accesses are then directly connected to the relevant storage and systems. A real-time monitoring system continuously monitors the network cloud resources and a periodic scanning system checks the resources at regular intervals. Both transmit the collected data to the GCN model within the protection system. The GCN model analyzes the data and, once it identifies anomalies, feeds the information to the defense mechanism (which triggers security defenses) and the access control module (which regulates access). The study employs the stochastic gradient descent technique to optimize the detection model's training process in an attempt to maximize the iterative impact of the intrusion detection method on the data content. Equation (2) illustrates the gradient descent method's algorithmic iteration law.

$$\theta_{i+1} = \theta_i - \alpha_i \nabla f_i(\theta_i) \tag{2}$$

θ_{i+1} represents the model's parameters at the $i+1$ th iteration in Equation (2). θ_i stands for the model's current iteration's parameters. The learning rate is shown by α_i. The gradient of the loss function with respect to the parameter θ_i is shown by the symbol $\nabla f_i(\theta_i)$. The stochastic gradient descent approach can be used to lessen the objective function's computing load during the training phase. More efficient data iteration is achieved by transforming the actual descending gradient process into descending estimation through stochastic approximation assignment.

2.3 Network resource security operational performance prediction

After constructing a resource scheduling framework under security constraints, this study further explores how to integrate the AM with the Transformer architecture by fusing it. This is to realize the accurate prediction of the security operation performance of network resources [19]. The effectiveness of secure scheduling decisions relies on accurate prediction of future network states. Therefore, the study establishes the model architecture for predicting the secure operation performance of network resources by fusing the AM, as displayed in Figure 5.

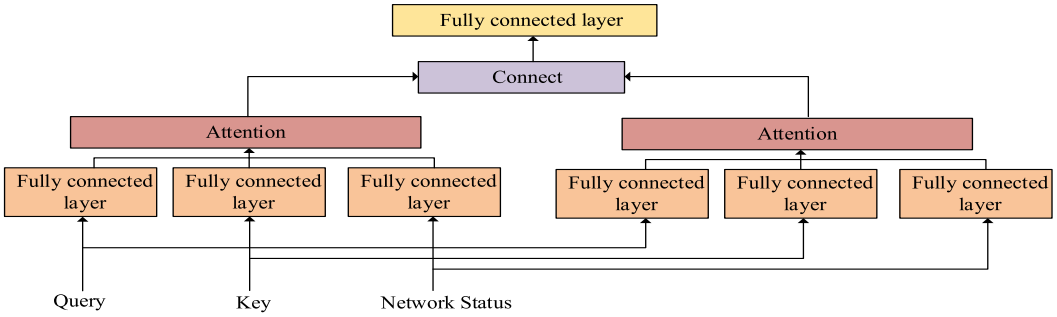


Figure 5: Architecture of a secure operational performance prediction model for network resources incorporating the AM

Figure 5 presents the model structure of the fused AM, where the inputs contain Query, Key, and Network Status that characterizes the network state. These inputs are first processed through the full connectivity layer separately to extract features initially. Subsequently, the AM module focuses on the key information, highlights the features that are important for predicting the secure operational performance of network resources, and weakens the irrelevant information. Next, the processed information is integrated by Connect operation. Finally, the information

is input to the full connectivity layer for comprehensive analysis and prediction to realize accurate judgment on the safe operation performance of network resources. The deep interaction between the multi-layer feed-forward network (FFN) and the multi-head (MH) AM further enhances the mining of the intricate temporal relationship between the security risk patterns and the multi-dimensional data of network resources when it is realized that the AM should concentrate on the important characteristics. Figure 6 displays the Transformer-based network resource security operation performance prediction model.

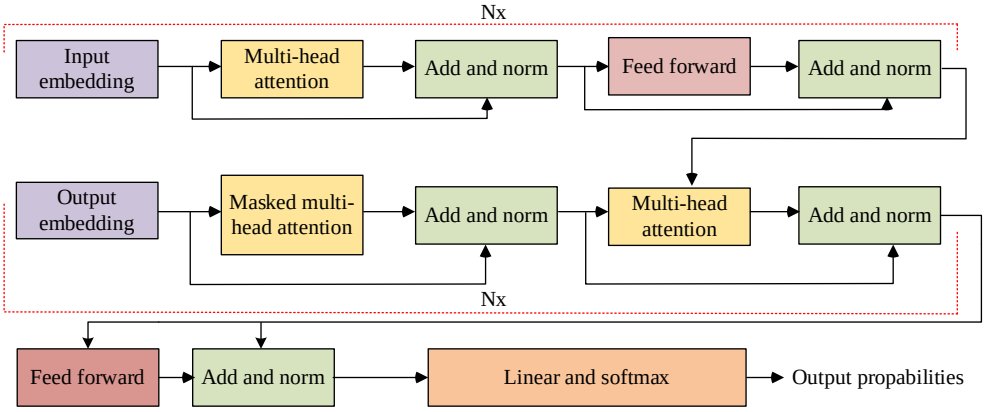


Figure 6: Transformer-based performance prediction model for secure operation of network resources

In Figure 6, the input embedding transforms the multidimensional data of the web resource into an embedded representation that the model can handle. The multi-AM is responsible for capturing the complex associations between different dimensions of data of network resources. It mines the key factors and potential patterns that affect the performance of network security operations. Feedforward network further processes the information processed by the AM. It learns the nonlinear features of network resource data to provide richer feature representation (FR) for performance prediction [20]. Through multiple layers of repeated attention and feedforward computations, the model learns network resource characteristics in depth. The output part is processed by linear transformation (LT) and Softmax to output the predicted probability of the safe operation performance of network resources, thus realizing the prediction of the safe operation state of network resources.

The Transformer architecture's standard self-attention and FFN layers form the foundation of the model. However, its application in this work is specifically tailored for multitask time series forecasting within a multicloud environment. The model utilizes a shared encoder with multiple task-specific heads to concurrently predict three key metrics essential for scheduling: task runtime, energy consumption, and failure risk.

A key architectural modification involves integrating causal convolution layers before the MH self-attention module. This adaptation is critical for effectively processing the time-series data streams from telemetry, such as CPU utilization and network traffic. Causal convolutions are adept at capturing local patterns and short-term temporal dependencies. This is crucial for reacting to sudden load shifts. The model achieves higher prediction accuracy under volatile workloads by combining the local feature extraction capabilities of causal convolutions with the long-range dependency modeling of self-attention. This enhanced predictive capability gives the SBSAD scheduler more reliable and timely information, which improves the quality of its dynamic resource allocation and scheduling decisions.

In the end, the outcomes of the MH AM and completely linked FFN's processing are used to forecast the network resources' safe operating performance. The study names the proposed model as SBSAD.

The SBSAD scheduler operates in a compact single-pass loop. Tasks are mapped to deadline buckets via fixed cutoffs. Online predictions are produced for runtime, energy, and failure risk. A GCN then computes feasibility masks that encode isolation and affinity/anti-affinity before placement. A single priority $P = a/(d - \text{now}) + bs + cD - d\hat{t}$ ranks tasks within each bucket, where d is the deadline, s the security level, D a dependency penalty. $\hat{t}$ the predicted runtime. Constants a, b, c, d are fixed on validation data. The scheduler places the highest-priority feasible tasks under capacity constraints and updates the capacity state. When telemetry indicates degradation or an imminent deadline risk, the scheduler promotes the affected tasks and preempts the lowest-priority ones. Observed durations then feed back to update the predictors.

3 Resource management and performance test results based on AI algorithms

For internal consistency and clarity, all reported results follow a single policy. Unless otherwise stated, percentages denote relative change versus the corresponding baseline and are computed as $\Delta\% = 100 \times (Baseline - Method) / Baseline$. Absolute

differences are labeled "Δ abs". Time-related metrics (response/turnaround) are reported in milliseconds (ms), energy in joules per task (J/task) obtained by integrating host power over time, throughput in tasks/s, and deadline satisfaction as a percentage (%). Values are rounded to one decimal place for percentages, times, and energy, and to the nearest integer for counts. Table totals and ratios are recomputed from unrounded means to avoid rounding drift. Unless noted otherwise, confidence intervals refer to 95% Student-t intervals over 20 seeds, and arrows in tables indicate the preferable direction (↓ latency/energy, ↑ satisfaction/throughput). Baselines use identical traces, capacity limits, and policy constraints to enable consistent comparisons within the same measurement context.

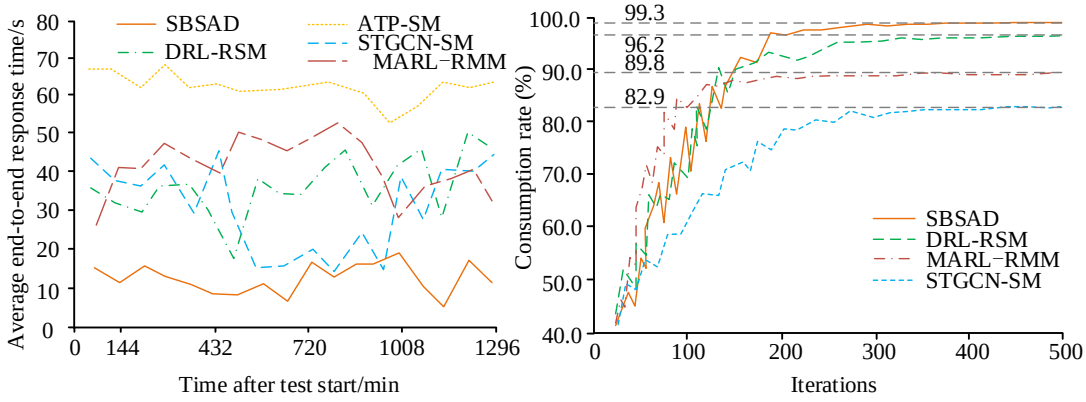
3.1 MC resource management scheduling results

To enhance reproducibility, the experimental setup is summarized concisely in Table 2.

Table 2: CloudSim environment, workload, variability, and evaluation (concise summary)

Category	Item	Setting
Simulator	Platform	CloudSim (datacenter, VM, cloudlet, network modules)
Topology	Datacenters & Hosts	3 datacenters; 100 hosts each
Hosts	Type S / Type L	S: 16 vCPUs @2.5 GHz, 64 GB RAM, 1 Gbps; L: 32 vCPUs @2.5 GHz, 128 GB RAM, 10 Gbps
Scheduling	Host / Cloudlet	TimeShared host VM scheduler; TimeShared cloudlet scheduler
VMs	t1 / t2 / t3	t1: 2 vCPUs, 4 GB, 2,000 MIPS; t2: 4 vCPUs, 8 GB, 4,000 MIPS; t3: 8 vCPUs, 16 GB, 8,000 MIPS
Placement	Capacity & Policy	Capacity-limited with isolation and affinity/anti-affinity rules
Workload	Mix & Lengths	60% CPU-bound, 20% I/O-bound, 20% mixed; log-normal lengths (median 3×1093\times10^9 MI, σ=0.6\sigma=0.6)
I/O	Input/Output Size	50–500 MB
Arrivals	Process	Poisson arrivals at 6 tasks/s
Deadlines	Setting	Per-task deadline =1.2× predicted runtime (non-trivial but feasible pressure)
Security	Levels	$s \in \{1,2,3\}$ used for isolation/affinity constraints
Telemetry	Updates	Online metrics refresh predictions for runtime, energy, failure risk
Variability	Load & Network	Aggregate load $\{0.5\times,1.0\times,1.5\times\}$ of host capacity; latency mean 3 ms (SD 1 ms)
Failures	Injection	Disabled (avoid confounding); predicted risk still consumed by scheduler
Repetitions	Seeds & runs	20 random seeds per load → 60 runs total
Metrics	Primary	Turnaround time, deadline satisfaction rate, energy per task, preemption count
Baselines	Fairness Controls	Identical capacity limits, policies, and workload traces across all policies

The study selects deep reinforcement learning-driven resource scheduling model (DRL-RSM), spatio-temporal graph convolutional network-based scheduling model (STGCN-SM), multi-agent reinforcement learning resource management model (MARL-RMM), attention-fused transformer for prediction and scheduling model (ATP-SM), and the proposed SBSAD method for comparison. The experiment relies on a high-performance server configured with Intel Xeon Gold 6248 processor, 128GB RAM, and NVIDIA Tesla V100 GPU. The operating system is Ubuntu 18.04. A MCE is constructed with the help of the CloudSim simulation platform, which accurately simulates the dynamic changes of the cloud resources and task loads. The performance comparison of different models in MC resource management scheduling is shown in Figure 7.



(a) Average end-to-end response time of different models changes with test time

(b) Consumption rate of different models changes with the number of iterations

Figure 7: Performance comparison of different models in MC resource management scheduling

In Figure 7(a), the average end-to-end response time (AETERT) of the research-proposed SBSAD method is relatively low at different test time points. This indicates that it is able to respond to tasks more quickly in MC resource management scheduling. It effectively improves the scheduling delay and has a significant advantage over other models. Figure 7(b) presents the variation of different model consumption rates with the number of iterations.

To provide a robust evaluation, the performance of the proposed SBSAD model is compared against four baseline models under identical experimental conditions. All reported results are mean values averaged over 20 independent runs. The standard deviation (SD) is included to indicate the consistency and reliability of the measurements. This statistical approach guarantees that the differences observed between models are significant and not the result of random variation. The key performance metrics are summarized in Table 3.

Table 3: Comparative performance metrics of scheduling models (Mean±SD over 20 runs)

Metric	SBSAD (Proposed)	DRL-RSM	STGCN-SM	MARL-RMM	ATP-SM
Turnaround time (ms) ↓	118.4±5.2	145.7±9.8	162.1±11.5	155.3±13.1	151.8±10.4
Deadline satisfaction (%) ↑	96.2±1.8	88.5±3.5	85.4±4.1	87.1±4.8	89.3±3.2
Energy per task (J/task) ↓	25.6±1.1	31.2±2.4	34.8±2.9	33.5±3.2	30.7±2.1
Preemption count ↓	15.3±2.5	45.8±6.7	51.2±7.2	60.1±8.5	41.5±6.1

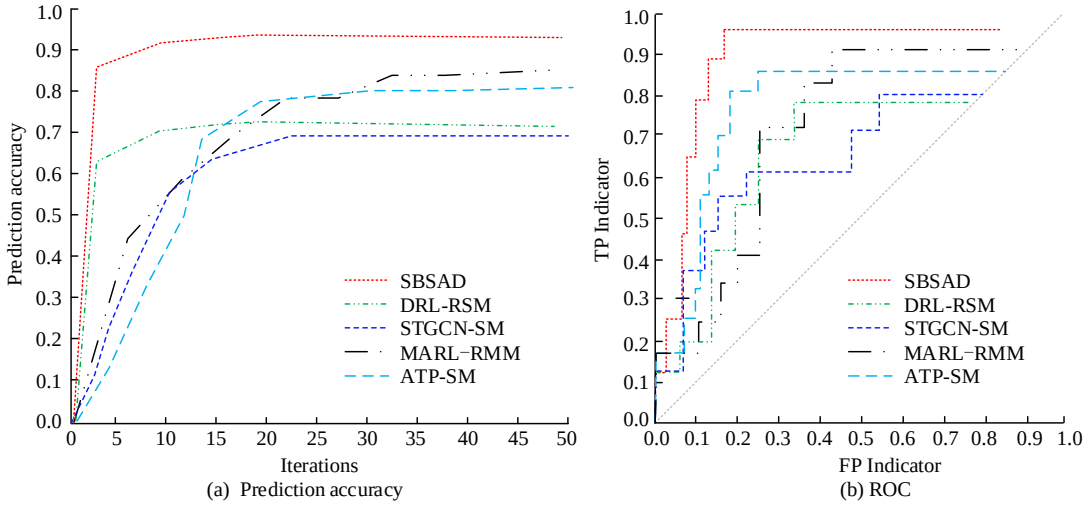
Note: Arrows (↓↑) indicate the preferable direction for each metric.

The aggregated results in Table 3 clearly demonstrate the superior performance of the SBSAD model across all evaluated metrics. With an average turnaround time of 118.4 ms, SBSAD significantly outperforms the next best baseline, DRL-RSM, which has an average turnaround time of 145.7 ms. Furthermore, its deadline satisfaction rate is the highest at 96.2%, indicating its effectiveness in meeting task constraints. The model is also more efficient. It has the lowest energy consumption per task (25.6 J/task) and a drastically reduced preemption count (15.3), compared to all other methods. The small standard deviations associated with SBSAD's metrics across the 20 runs underscore the consistency and stability of its performance, thereby reinforcing the statistical significance of these improvements.

3.2 Results of predicting the operational performance of network resource security management

For clarity, model names are abbreviated as follows: DRL-RSM (deep-reinforcement-learning resource scheduling model), STGCN-SM (spatio-temporal graph convolutional scheduling model), MARL-RMM (multi-agent reinforcement-learning resource management model), and ATP-SM (attention-based Transformer scheduling model). Representative implementations and citations are summarized in related work.

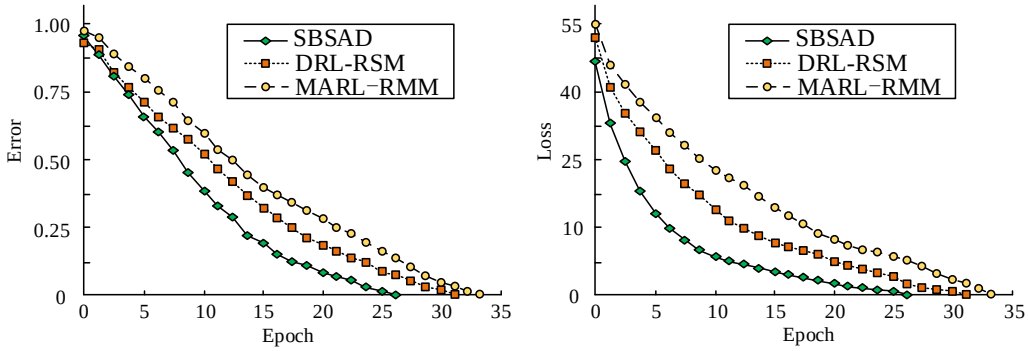
The study tested the above models on two datasets, CloudSim Simulation Dataset (CloudSim Dataset) and BigDataBench: Big Data Benchmark (BigDataBench). A comparison of the results of the predicted operational performance of security management of network resources for different models is shown in Figure 8.



(a) Prediction accuracy (b) ROC

Figure 8: Comparison of operational performance prediction results of different models for network resource security management Abbreviations: DRL-RSM=deep-reinforcement-learning resource scheduling model; STGCN-SM=spatio-temporal GCN scheduling model; MARL-RMM=multi-agent RL resource management model; ATP-SM=attention-based Transformer scheduling model.

The prediction accuracy for various models varies with the quantity of iterations, as shown in Figure 8(a). The SBSAD method proposed in the study shows a rapid increase in prediction accuracy and stabilizes at a high level during the iteration process. Compared with other models, it can learn the patterns of network resources' secure operation performance more quickly and precisely, and significantly improve the prediction accuracy. The ROC curve analysis in Figure 8(b) shows that the curve of SBSAD is located at the top. It means that SBSAD has a higher true positive indicator with the same false positive indicator (FP Indicator). It can more effectively identify the real state of network resource security operation and reduce the misjudgment situation. The variation of error and loss of each model with training rounds under different datasets is shown in Figure 9.



(a) CloudSim Dataset (b) BigDataBench

Figure 9: Variation of error and loss with training rounds for each model under different datasets Abbreviations: DRL-RSM=deep-reinforcement-learning resource scheduling model; STGCN-SM=spatio-temporal GCN scheduling model; MARL-RMM=multi-agent RL resource management model; ATP-SM=attention-based Transformer scheduling model.

Figure 9(a) demonstrates the variation of error with training rounds for different models on CloudSim Dataset. Figure 9(b) demonstrates the variation of loss with Epoch for different models on BigDataBench. The error of SBSAD method proposed in the study decreases rapidly with increasing Epoch on CloudSim dataset. Compared to the rest of the models, it has a lower final error value and more accurate prediction. On the BigDataBench dataset, the loss value of SBSAD decreases rapidly. Moreover, under the same Epoch, the loss value is lower than the other models. Its training effect is better and it can learn the characteristics of network resource security management operation performance more efficiently. Table 4 displays the performance forecast results for the security scheduling operation and MC resource management.

Table 4: Predicted performance of MC resource management and secure scheduling operations

Test scenario	Scheduling model	Network bandwidth utilization (%)	Task scheduling rate improvement (%)	Task quantity reduction	Prediction accuracy improvement (%)	Predicted response time (ms)	System stability (%)
Scenario 1	SBSAD and multi-task learning model	85.27	6.52	18	14.8	110.65	97.89
Scenario 2	Traditional scheduling method	81.58	0.00	0	0	124.32	94.35
Scenario 3	SBSAD and multi-task learning model	89.12	6.52	18	14.8	105.21	98.03
Scenario 4	Traditional scheduling method	77.63	0.00	0	0	131.54	93.12

Interpreting Table 4, performance gains are linked to where SBSAD changes the decision process rather than to aggregate scores alone: The DQN-informed estimates reduce queueing and late starts. This contributes to the 6.52% increase in deadline satisfaction despite identical capacity limits. GCN-derived feasibility masks eliminate security and affinity conflicts before packing. This explains why the number of required scheduling tasks is reduced by 18 and why stability is higher. The attention-based, multi-task predictor reduces runtime prediction error by 14.8%. This results in shorter predicted response times and fewer preemptions. Improvements in bandwidth utilization (e.g., 85.27%–89.12% in Scenarios 1–3) reflect conflict-aware placement rather than mere over-commitment. Note that some VM-level entries in Table 2 favor DRL-RSM for isolated metrics, such as single-VM delay. However, end-to-end turnaround time and deadline satisfaction favor SBSAD because it handles conflicts and risk prior to packing.

4 Discussion

Using the identical traces and capacity controls described in Section 4, SBSAD decreased the end-to-end turnaround time and increases the satisfaction rate of meeting deadlines, while reducing the number of late or dropped tasks and preemptions. These gains stemmed from stage-based deadline bucketing and a single scalar priority that considered urgency, security, dependency, and predicted runtime. This was in contrast to DRL-RSM, where reward shaping and global queues make deadline pressure less explicit. Unlike STGC-SM that relied on static graph features or offline prediction, STGC-SM directly consumed online multitasking prediction (runtime/energy/fault risk) within the scheduler.

Therefore, its response to short-term load changes was slower. Moreover, by preempting cost feedback for cross stage promotion, it avoided the convergence overhead observed in the sudden arrival of MARL-RMM. In practical cloud stacks, integration was straightforward: In Kubernetes, a scheduler framework plugin or extender could replace the native scoring with a scalar priority while applying GCN-derived feasibility masks in the filter phase. The predictor was deployed as a telemetry-driven sidecar. Equivalent behavior in OpenStack-like platforms followed from custom host filters and weights. Operational interpretation revealed that improved accuracy reduced queue build-up and deadline violations for batch and ML workflows in shared clusters. It also lowered interference in isolation-critical, multi-tenant SaaS and stabilized edge-to-cloud video and ETL pipelines during short-term surges. Limitations remain: Reliance on predictor quality and stable telemetry can bias prioritization. The CloudSim environment simplifies network and storage contention compared to production systems. Preemption cost and fairness are modeled beyond deadline satisfaction at a coarse level. These factors define low-risk deployment zones and indicate where additional engineering hardening or A/B trials are recommended.

Future work will entail evaluating SBSAD on production-like clusters with realistic network and storage contention. Additionally, the predictor will be augmented with calibrated uncertainty to de-bias the priority score under telemetry drift. Furthermore, fairness and preemption cost will be incorporated into a multi-objective function that goes beyond deadline

satisfaction. Finally, cross-cluster portability and autoscaling interactions in Kubernetes and OpenStack deployments will be studied to broaden applicability.

5 Conclusion

This study introduced the SBSAD model, an AI-driven framework that improved MC resource management. The model integrated a DQN for parameter estimation, a GCN for security policy enforcement, and a Transformer for multi-task performance prediction. The experimental results showed that the SBSAD method significantly improves scheduling performance. It reduced the AETERT by 15%-20% and increased the task scheduling rate by 6.52%, compared to baseline models. Furthermore, the model improved prediction accuracy by 14.8% while maintaining system stability above 97.89%.

Although the proposed approach shows promise, future work should address its current limitations, such as its adaptability to heterogeneous environments and its ability to generalize against novel threats. Future optimizations will focus on lightweight neural network architectures and introducing federated learning to improve the practical, real-world applicability of secure MC systems.

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ILS-YOLO: An Improved List Scheduling Algorithm for YoloLite DAGs in Vehicular Edge Computing

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Real-time vehicle detection is critical for intelligent transportation systems, yet deploying lightweight models like YoloLite on resource-constrained vehicular units leads to prohibitive latency. To address this challenge, this paper introduces ILS-YOLO, an Improved List Scheduling algorithm for YoloLite Directed Acyclic Graphs (DAGs) in Vehicular Edge Computing (VEC). The algorithm models the YoloLite inference pipeline as a DAG of sub-tasks and introduces two key innovations: a Unified Scheduling Table to mitigate resource fragmentation on multi-core edge servers and a Transfer Scheduling Table to accurately model link contention and communication overhead. Performance is evaluated through extensive simulations using synthetic DAGs with varying structures (up to 200 nodes) and Communication-to-Computation Ratios (CCRs), alongside a case study using parameters derived from a complex perception task and real-world traffic data. Results show that ILS-YOLO significantly reduces end-to-end detection latency, achieving a speedup of up to 2.5× over baseline scheduling heuristics for large, computation-intensive DAGs (n=200, low CCR). This work presents a robust and efficient scheduling solution that makes low-latency, high-accuracy vehicle detection feasible in practical VEC environments.

Povzetek: Študija predstavi algoritem ILS-YOLO, ki z izboljšanim razporejanjem podopravil v VEC-okolju močno zmanjša zakasnitev pri YoloLite zaznavi vozil in doseže do 2,5-kratno pohitritev glede na klasične heuristike.

1 Introduction

Automobile edge detection systems have gained prominence with the rapid development of intelligent transportation systems and autonomous driving technologies [1]. These systems demand real-time and precise vehicle detection to enable safe and efficient traffic management and autonomous navigation. However, the computational requirements of advanced detection algorithms often surpass the capabilities of vehicle onboard units. Vehicular Edge Computing (VEC) emerges as a solution, allowing vehicles to offload computation-intensive tasks to nearby edge servers. This paradigm enhances computational power and reduces latency, making real-time vehicle detection feasible. Recent works like Sihai Tang et al. and Yu-Jen Ku et al. have demonstrated the potential of VEC in improving multi-vehicle perception and minimizing end-to-end delay [2,3]. A review of traditional edge detection methods reveals their applications in various fields including autonomous vehicles, where edge detection and segmentation are crucial for detecting motion and tracking video.

Traditional vehicle detection methods primarily relied on local processing within the vehicle's onboard unit. While this approach ensures data privacy and offline functionality, it struggles with the computational demands of modern deep learning models. Studies such as Li et al. highlight the limitations of traditional methods in achieving real-time performance [4]. Local processing often results in significant latency, especially during peak traffic periods or complex traffic scenarios, hindering the system's ability to provide timely and accurate detection results. Traditional edge detection algorithms generally adopt differential methods for calculation. Common first-order differential edge detection operators include Robert, Sobel, Prewitt, and Kirsch operators, which are simple and fast in calculation but less accurate in positioning [5]. Second-order differential operators, such as Canny, Log, and Laplacian operators, locate edges accurately but are sensitive to noise [6]. For noise-polluted images, filtering is usually performed before differential edge detection to minimize noise impact, but this can also blur image edges to some extent. The Marr operator combines noise filtering with edge extraction, but it has poor noise resistance when the template is small and is time-consuming when the template is large [7].

Current optimization strategies in vehicle detection technology have been advanced through various approaches. Satzoda and Trivedi focused on the dynamics of rear lights for vehicle detection at night, improving detection accuracy under low-light conditions

[8]. Yan et al. combined HOG with AdaBoost classification to achieve real-time vehicle detection, enhancing the speed and accuracy of the detection process [9]. Concurrently, advanced deep reinforcement learning techniques, such as attention-augmented multi-agent algorithms, are being employed to manage complex resource allocation in NOMA-based vehicular systems [10]. Furthermore, these optimization strategies are being extended to emerging collaborative scenarios, such as UAV-assisted vehicle platooning, to ensure efficient task processing and resource management across multiple platforms [11]. These strategies collectively contribute to more efficient, accurate, and real-time vehicle detection systems.

This study addresses these challenges by proposing the Improved List Scheduling for YoloLite DAGs (ILS-YOLO) algorithm. The ILS-YOLO algorithm models the YoloLite inference process as a Directed Acyclic Graph (DAG) and introduces a Unified Scheduling Table and a Transfer Scheduling Table. These innovations aim to optimize resource utilization and communication efficiency, minimizing end-to-end detection latency. Unlike existing methods that often treat applications as atomic tasks, our approach provides a more fine-grained and efficient scheduling strategy by considering the pipeline's dependencies and workload characteristics.

The remainder of this paper is organized as follows: Section 2 describes the problem and formulates the mathematical model. Section 3 details the proposed ILS-YOLO algorithm. Section 4 presents the numerical experiments and discusses the results. Finally, Section 5 concludes the paper and suggests directions for future research.

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2 Related work

2.1 Task offloading in vehicular networks

Task offloading is a cornerstone of Vehicular Edge Computing (VEC), enabling resource-constrained vehicles to execute computationally intensive applications by migrating them to more powerful edge servers. The primary goal of task offloading is to optimize one or more performance metrics, such as latency, energy consumption, or computational cost. The research landscape for task offloading is diverse, addressing various scenarios from simple single-user, single-server setups to complex multi-user, multi-server environments with cloud integration.

Early research often focused on single-edge-server scenarios. In these models, a group of vehicles communicates with a single Roadside Unit (RSU). Mao et al. [12] utilized Lyapunov optimization to minimize a weighted sum of processing delay and task failure costs under energy constraints. Wang et al. [13] proposed an online task scheduling method for vehicular edge computing based on imitation learning to achieve near-optimal performance. To address the trade-off between latency and energy consumption, researchers have widely applied Deep Reinforcement Learning (DRL). Zhan et al. [14] utilized DRL to optimize offloading scheduling in vehicular edge computing, while Zhou and Hu [15] focused on maximizing computation efficiency in wireless-powered mobile edge computing networks. To better capture the dynamic characteristics of the vehicular environment, Liu et al. [16] developed a dependency-aware task scheduling model to handle complex tasks with interdependencies.

Furthermore, some researchers have investigated three-tier architectures that integrate a remote cloud layer with the edge-vehicle layers. This cloud-edge-end collaborative paradigm allows tasks to be offloaded to either the edge for low latency or the cloud for massive computational power. For example, Wu et al. [17] proposed an efficient task scheduling algorithm for servers with dynamic states in vehicular edge computing. Li et al. [18] introduced a multi-objective-oriented task scheduling method to balance multiple performance metrics in heterogeneous networks. Distributed approaches have also been explored to enhance scalability, with Tang and Wong [19] introducing a distributed DRL algorithm that allows each mobile device to make decentralized decisions based on local observations.

Furthermore, some researchers have investigated three-tier architectures that integrate a remote cloud layer with the edge and vehicle layers. Geng et al. [20] developed a DRL-based distributed computation offloading framework to leverage the advantages of collaborative edge-cloud computing. A summary of representative works is presented in Table 1.

While these works have laid a strong foundation for VEC task offloading, many treat applications as atomic, indivisible tasks. Our work differs by specifically addressing applications like real-time object detection, which can be decomposed into a pipeline of dependent sub-tasks. By modeling this pipeline as a Directed Acyclic Graph (DAG), we can achieve a more fine-grained and efficient scheduling of computational resources to minimize end-to-end latency.

Table 1: Summary of optimization objectives, constraints, and proposed solutions

Literature	Optimization Objective	Constraints	Proposed Solution
[1]	Weighted sum of processing delay and task failure cost	Battery output power	Method based on Lyapunov optimization
[2]	Energy consumption	Cache task size	Method combining block coordinate descent and convex optimization
[3]	Weighted sum of processing	Maximum task	Method based on Q-learning and DQN

	delay and energy consumption	processing deadline	
[4]	Energy consumption	Maximum task processing deadline	Method based on Q-learning and DDQN
[5]	Task processing latency	Maximum task processing deadline	Method combining RNN with deep reinforcement learning
[6]	Weighted sum of processing delay and energy consumption	Maximum task processing deadline	End-to-end deep reinforcement learning model
[7]	Weighted sum of processing delay and energy consumption	Maximum task processing deadline	Algorithm based on Q-learning
[8]	Weighted sum of processing delay and task discard penalty	Queue state of device and edge node	Algorithm combining LSTM with Dueling DDQN
[9]	Weighted sum of processing delay and energy consumption	Maximum task completion deadline, device power limit	Algorithm combining LSTM with deep reinforcement learning

2.2 Dag-based task scheduling in heterogeneous computing environments (review of heft, peft, etc.)

Scheduling tasks with dependencies, modeled as a Directed Acyclic Graph (DAG), onto a set of heterogeneous processors is a well-known NP-hard problem [11]. Consequently, a plethora of heuristic and meta-heuristic algorithms have been developed to find near-optimal solutions in polynomial time. These algorithms are crucial for applications like the YoloLite pipeline, where sub-tasks have precedence constraints.

List scheduling is one of the most prominent categories of heuristics due to its simplicity and effectiveness. These algorithms typically operate in two phases: a task prioritization phase and a processor selection phase. The Heterogeneous Earliest Finish Time (HEFT) algorithm, is a benchmark in this category [21]. HEFT prioritizes tasks based on their upward rank, which represents the length of the critical path from a task to the exit node, including both computation and communication costs. It then assigns each task to the processor that minimizes its earliest finish time, using an insertion-based policy that effectively utilizes idle time slots.

Building upon HEFT, several variants have been proposed to improve scheduling quality. The Predict Earliest Finish Time (PEFT) algorithm [22] enhances the processor selection phase by introducing an optimistic cost table (OCT). The OCT provides a lookahead mechanism by estimating the time from a given task to the end of the entire DAG, allowing for more informed scheduling decisions without increasing the algorithm's time complexity. Other approaches have focused on task duplication to eliminate communication overhead by executing a task's predecessors on the same processor, though this comes at the cost of redundant computation. Clustering-based methods, which group tasks to be executed on the same processor, have also been explored, but list scheduling often provides a better trade-off between performance and complexity. Our work adapts the core principles of list scheduling, specifically HEFT, to the unique constraints of the VEC environment, such as contended communication links and multi-core edge servers.

2.3 Reinforcement learning for resource management in edge computing

Reinforcement Learning (RL) provides a powerful framework for solving sequential decision-making problems under uncertainty, making it highly suitable for resource management in dynamic edge computing environments. Unlike traditional optimization methods that may require a precise system model, RL agents learn optimal policies through direct interaction with the environment. In the context of DAG scheduling, RL can be used to navigate the vast search space of possible task-to-processor mappings. Compared to RL-based methods [23, 24], ILS-YOLO leverages deterministic heuristics for faster, reproducible scheduling, avoiding RL's training overhead and hyperparameter sensitivity. While RL excels in dynamic environments, our approach prioritizes predictable performance for real-time VEC, as validated by comparisons against HEFT and PEFT Chen et al. [23] modeled the dependent task offloading problem as a Markov Decision Process (MDP) and proposed a DRL-based approach that jointly considers task topology and wireless channel interference. Similarly, Song et al. [24] formulated DAG offloading as a multi-objective optimization problem and developed an RL method to balance latency, energy, and cost.

A key challenge in applying RL to DAG scheduling is the "curse of dimensionality." The state-action space grows exponentially with the number of sub-tasks in the DAG and the number of available processors. For a DAG with $|V|$ tasks and $|P|$ processors, the number of possible scheduling policies can be immense, making it intractable for tabular RL methods like basic Q-learning to explore the environment effectively. This often leads to excessively long training times and convergence to suboptimal policies, as the agent fails to visit a representative sample of state-action pairs.

To mitigate this, our research adopts a hybrid approach that combines RL with a strong heuristic. By using an

established algorithm like HEFT to provide a baseline policy, we can effectively prune the search space. The RL agent's role shifts from learning a policy from scratch to learning a residual correction—identifying specific situations where deviating from the heuristic's greedy choice leads to a better long-term outcome. This synergy allows the RL agent to focus its exploration on the most promising regions of the solution space, which dramatically accelerates convergence and retains the ability to discover schedules superior to the baseline heuristic.

2.4 Lightweight object detection models for edge devices

The proliferation of real-time perception tasks in autonomous systems has driven the development of lightweight deep neural networks (DNNs) optimized for resource-constrained edge devices. While highly accurate models like the original YOLO [25] provide excellent performance, their computational and memory footprints are often too large for deployment on vehicular onboard units. This has led to a family of efficient architectures, such as MobileNets, SqueezeNets, and various YOLO variants (e.g., YOLO-tiny, Nano-YOLO). YoloLite [26, 27, 28] represents a specific effort in this direction, aiming to drastically reduce model complexity while maintaining acceptable accuracy for tasks like vehicle detection.

Furthermore, the core challenge of dynamic resource allocation in VEC shares conceptual parallels with problems in robust control theory, where the goal is to maintain system stability and performance under uncertainty. While the technical domains are distinct, the underlying principle of adaptive optimization provides a valuable high-level inspiration. For instance, sophisticated methodologies such as adaptive fuzzy control for chaotic and interconnected systems [29], output-feedback controllers for uncertain chaotic systems [30], robust neural adaptive control for complex multivariable systems [31], and adaptive backstepping control for uncertain nonlinear systems [32, 33] all demonstrate powerful frameworks for achieving optimal control in dynamic environments. These advanced control strategies, along with nonlinear optimal control approaches [34], although not directly applicable to DAG scheduling, inform the broader objective of developing intelligent and adaptive solutions for real-time resource management in unpredictable settings like vehicular networks.

These lightweight models achieve their efficiency through a variety of architectural innovations. Techniques such as depthwise separable convolutions, which factorize a standard convolution into two smaller layers, significantly reduce the number of parameters and floating-point operations (FLOPs). Other methods include using bottleneck layers with 1x1 convolutions to reduce channel dimensions, aggressive network pruning to remove redundant weights, and post-training quantization to represent weights with lower-bit integers. These optimizations create a critical trade-off between model accuracy, inference latency, and energy consumption, which must be carefully managed by system designers.

Even with these optimizations, the inference process of a lightweight model is not a monolithic block of computation. It remains a complex pipeline of distinct operational stages, such as a feature extraction backbone, a feature fusion neck (e.g., FPN, PAN), and multiple detection heads for predictions at different scales. Each stage has heterogeneous computational requirements. For example, the backbone may be computationally intensive but highly parallelizable, while post-processing steps like Non-Maximum Suppression (NMS) are typically sequential and latency-sensitive. By decomposing this pipeline into a DAG, we can exploit this heterogeneity through fine-grained offloading. This enables a strategic mapping of sub-tasks to the most suitable computational resource—vehicle or edge—thereby meeting strict real-time latency constraints that would be impossible to achieve with naive, all-or-nothing offloading.

3 System model and problem formulation

This chapter provides a comprehensive and formal definition of the system architecture, the application task model, and the underlying computation and communication models tailored to the VEC environment. We delve into the intricacies of resource contention and scheduling on both communication links and multi-core processors. Finally, we formulate the DAG scheduling challenge as a makespan minimization problem, establishing the theoretical foundation for the algorithms presented in the subsequent chapter. A list of key notations used throughout this chapter is summarized in Table 2. The system model comprises three key layers: (1) the vehicle's Onboard Unit (OBU) as the local server s_0, responsible for initial data capture and lightweight processing; (2) Roadside Units (RSUs) as edge servers $s_1, \ldots, s_{m-1}$, providing low-latency computation near the vehicle; and (3) the cloud server s_m, offering high computational power for intensive tasks. Interactions occur via wireless V2I links between OBU and RSUs, and wired/fiber links between RSUs and the cloud.

Table 2: Notations and their meanings

w_i	Subtask v_i
$\mathrm{pred}(v_i)$	Set of predecessor subtasks of subtask v_i
f_j	Processing frequency of the computational unit of server s_j
$n_{\max}^{j}$	Number of computational units of server s_j
$t_{\mathrm{calc}}^{i,j}$	Computational latency of subtask v_i on server s_j

$t_{\text{trans}}^{i,j,k,l}$	Transmission latency for data from v_i to v_k transmitted from server s_j to s_l
$t_{\text{prop}}^{k,l}$	Propagation latency from server s_k to s_l
$t_{\text{comm}}^{i,j,k,l}$	Total communication latency for transmitting data from v_i to v_k from server s_j to s_l
$r_{i,j}$	Data volume of the computational results that subtask v_i needs to transmit to v_j
x_i	Server allocated to subtask v_i
s_t^i	Start time of subtask v_i
f_t^i	End time of subtask v_i
$r_{t,i}$	Time when subtask v_i can begin processing

3.1 Vec architecture and resource

We consider a VEC architecture composed of a set of heterogeneous computational entities. Let $S = s_0, s_1, \ldots, s_P$ denote the set of all available servers (processors), where s_0 is the vehicle's onboard unit (OBU) and the remaining servers $s_1, \ldots, s_P$ are external resources, including RSUs at the edge and a remote cloud data center. Each server $s_j \in S$ is characterized by its computational capability and the number of its processing cores.

Computational resources: The processing capability of a server s_j is defined by its CPU frequency, f_j (measured in cycles per second). We explicitly model multi-core processors, which are common in edge and cloud servers. Let $n_j^{\max}$ be the number of identical CPU cores available on server s_j. This allows for the parallel execution of up to $n_j^{\max}$ independent sub-tasks on a single server. The heterogeneity of the system arises from the fact that both f_j and $n_j^{\max}$ can vary significantly across different servers (i.e., $f_j \neq f_k$ or $n_j^{\max} \neq n_k^{\max}$ for $j \neq k$).

Communication resources: Communication occurs over wireless links between the vehicle and RSUs (Vehicle-to-Infrastructure, V2I), and potentially wired links between edge servers and the cloud. We model the communication network as a set of links, where each link $l_{k,j}$ connecting server s_k to server s_j is characterized by its bandwidth $B_{k,j}$ and transmission power parameters. Crucially, these links are shared resources. If multiple data transfers are scheduled concurrently on the same link, they will experience queuing delays, a factor that is often overlooked in simpler models but is critical for accurately predicting latency in a VEC system.

Offloading resources: Offloading is a critical process for achieving efficient utilization of computational resources. As depicted in Fig.1, the offloading process consists of two key steps. First, the subtask to be offloaded is transmitted to the target server via a communication link. Once the transfer is complete, the subtask undergoes further processing on the server. Both steps may involve queuing due to resource contention. Specifically, when transmitting a subtask to another server, if the communication link has available resources, the transmission proceeds immediately; otherwise, the subtask is queued and waits for its turn. Similarly, upon arrival at the server, if computational resources are available, the subtask is processed immediately; otherwise, it is placed in a computation queue to await processing after prior subtasks are completed.

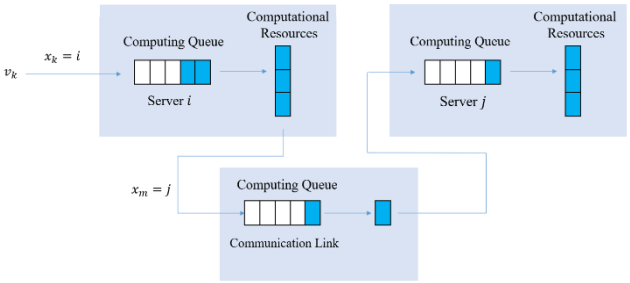

Figure 1: Offloading process

The problem is subject to the following assumptions:
1.A subtask can only be processed after all its predecessor subtasks have been completed.
2.Each computing unit can handle one subtask at a time, and processing cannot be interrupted once started.
3.Transmission of task results within the same server incurs no time cost.
4.A communication link can handle one transmission request at a time.
5.The start and end subtasks of a task are executed on the vehicle and do not consume computational resources.

3.2 Application model and latency formulation

We model the YoloLite application as a Directed Acyclic Graph（DAG）, $T = (V, E, W, R)$, which captures the intricate dependencies and workload characteristics of the inference pipeline, shown as Fig. 2. The set $V = v_{\text{start}}, v_1, \ldots, v_n, v_{\text{end}}$ contains nodes representing each computational sub－task. The set of directed edges, E, defines the dependencies, where an edge $e_{i,j}$ indicates that v_j depends on the output of v_i. The vector W contains the computational workloads w_i（in CPU cycles）for each sub－task, and the matrix R contains the data sizes $r_{i,j}$（in bits）to be transferred between dependent tasks. This fine－grained model allows us to move beyond coarse, all-or-nothing offloading and make intelligent decisions about where to place each individual stage of the YoloLite pipeline.

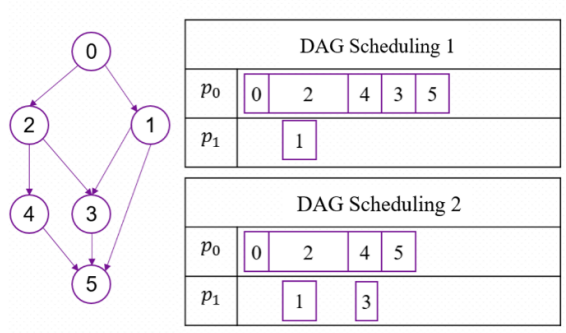

Figure 2: DAG scheduling examples

This study considers a computing environment consisting of N Roadside Units (RSUs) and one cloud server. Each RSU is associated with an edge server, and the set of all servers is denoted as $S = \{1,2,\cdots,N+1\}$. The processing frequency of server s_i is represented by f, and the number of computing units is denoted as $n_i^{\max}$. Let x_i represent the server assigned to subtask x_i, where $x_i = j$ indicates that the subtask is allocated to server s_j for processing. The communication link between servers s_i and s_j is denoted as $l_{i,j}$.

The start time of subtask v_i is denoted as st_i, and the finish time as ft_i, which can be calculated using the following equation:

$$ft_i = st_i + t_{i,x_i}^{\text{calc}} \tag{1}$$

Here, $t_{\text{calc}}(i,x_i)$ denotes the computational latency for subtask v_i on server s_{x_i}, calculated based on the subtask's workload and the server's processing frequency f_{x_i}. The finish time ft_i is linearly related to the start time st_i plus the overhead.

The start time of a subtask v_i depends on two factors: the time when the assigned server becomes available to process the subtask, avail$[x_i]$, and the time when all predecessor subtasks have transmitted their results to the server (ready time), denoted as rt_i. The ready time can be determined by the start time of the predecessor subtask's result transmission, $st_{i,j}$, as follows:

$$rt_i = \max_{v_m \in \text{pred}(v_i)} \{st_{m,j} + t_{m,i}^{\text{comm}}\} \tag{2}$$

Here, $t_{m,i}^{comm}$ represents the communication latency for transmitting the computational results from server S_m (where subtask v_m is located) to server s_i. Thus, the start time of the subtask is given by:

$$st_i = \max\{\text{avail}[x_i], rt_i\} \tag{3}$$

The availability avail (x_i) depends on the finish times of all previously allocated subtasks on server s_{x_i}, as tracked in the Unified Scheduling Table. This ensures that the server is free only after completing prior executions, modeling dependencies and preventing overlapping on the same core.

The objective of the problem is to minimize the task completion time, defined as $ft_n - st_0$. Consequently, the problem can be formulated as follows:

$$\begin{aligned} \min_x \quad & ft_n - st_0 \\ \text{s.t.} \quad & x_i \in S, \forall i \in \{1,2,\cdots,n\} \\ & st_i = \max\{\text{avail}[x_i], rt_i\}, \forall i \\ & rt_i = \max_{v_m \in \text{pred}(v_i)} \{st_{m,j} + t_{m,i}^{\text{comm}}\}, \forall i \\ & ft_i = st_i + t_{i,x_i}^{\text{calc}}, \forall i \end{aligned} \tag{4}$$

The objective function in Equation (4) minimizes the makespan by considering start times $st_i = \max(rt_i, \text{avail}(x_i))$. Here, rt_i captures delays from data dependencies, while avail(x_i) accounts for resource contention delays, ensuring all relevant overheads are modeled distinctly for clarity and accuracy. The makespan, measured in seconds (s), is defined as Makespan $= ft_{\text{end}} - st_{\text{start}}$, where st_{start} is the start time of the initial virtual task v_{start}, and ft_{end} is the finish time of the final virtual task v_{end}.

To accurately solve the scheduling problem, we must construct detailed models for both computation and communication latency that account for resource contention. The nominal execution time of a sub—task v_i on a server s_j with processing frequency f_j is defined as:

$$t_{i,j}^{calc} = w_i / f_j \tag{5}$$

However, the actual start time depends on resource availability. A naive approach of managing schedules for each core of a multi—core processor independently can lead to significant resource fragmentation, where a task may wait for a specific core despite other cores being idle. To address this, we introduce a Unified Scheduling Table for each server s_j. This mechanism tracks the total number of busy cores, $n_j(t)$, over time. A new task can be scheduled in the earliest time interval $[t_{\text{start}}, t_{\text{finish}}]$ where its data dependencies are met and a core is available $(n_j(t) < n_j^{\max}$ for the duration of the interval). This ensures efficient utilization of all available cores.

Similarly, communication latency must account for link contention. The theoretical data rate $d_{k,j}$ for a link $l_{k,j}$ between server s_k and s_j is given by the Shannon—Hartley theorem as

$$d_{k,j} = B_{k,j} \log_2 \left(1 + p_k^{\text{trans}} g_{k,j} / N_0\right) \tag{6}$$

where $B_{k,j}$ is bandwidth, p_k^{trans} is transmission power, $g_{k,j}$ is channel gain, and N_0 is noise power. In a realistic scenario, multiple data transfers contend for these links. We model each link as a single—server queue with a FIFO policy, managed by a Transfer Scheduling Table. The earliest a data transfer of size $r_{m,i}$ can start, $ST_{\text{comm}}(r_{m,i})$, is the maximum of when the data is produced by its predecessor, $FT(v_m, x_m)$, and when the link becomes available, avail $_{\text{link}}[k,j]$. The communication finish time is

$$FT_{\text{comm}}(r_{m,i}) = ST_{\text{comm}}(r_{m,i}) + (r_{m,i}/d_{k,j}) + t_{k,j}^{prop} \tag{7}$$

where $t_{k,j}^{prop}$ is the propagation delay, $ST_{\text{comm}}(m,i)$ is the link availability time from the Transfer Scheduling Table, $r_{m,i}/d_{k,j}$ is the transmission time based on data

volume and link bandwidth, and $t_{\text{prop}}(k,j)$ is the propagation delay.

This queuing model provides a realistic estimation of communication delays.

3.3. Adaptive and robust UKF variants

With these detailed models in place, the scheduling problem can be precisely formulated. The primary objective is to determine the optimal server assignment vector $X = [x_1, \ldots, x_n]$ and the corresponding start times that minimize the overall application completion time, or makespan. The scheduling process is regulated by two key factors for each subtask: the Earliest Ready Time (ERT) and the Earliest Start Time (EST).

The ERT for a subtask v_i on a potential server s_j is defined as the time when all necessary input data from its predecessor subtasks have arrived at s_j. This is determined by the finish time of the last arriving data packet, which can be formally expressed as:

$$\text{ERT}(v_i, s_j) = \max_{v_m \in \text{pred}(v_i)} \text{FT}_{\text{comm}}(r_{m,i}) \text{ on link } l_{x_m,j} \quad (8)$$

A task v_i cannot commence execution on server s_j before its $\text{ERT}(v_i, s_j)$ has been reached. The $\text{EST}(v_i, s_j)$ must satisfy both data readiness and processor availability. It is the earliest time t, which is greater than or equal to $\text{ERT}(v_i, s_j)$, at which a processing core on server s_j is available for the required duration $t_{i,j}^{\text{calc}}$. The Earliest Finish Time (EFT) is then simply calculated as:

$$\text{EFT}(v_i, s_j) = \text{EST}(v_i, s_j) + t_{i,j}^{\text{calc}} \quad (9)$$

The makespan of the entire schedule is determined by the finish time of the final virtual task, v_{end}, which is the maximum of the finish times of all its predecessor tasks. The optimization problem is therefore to minimize this makespan, $\text{FT}(v_{\text{end}}, x_{\text{end}})$, subject to all precedence and resource constraints. Formally, the problem can be stated as follows:

Minimize: Makespan(X)

Subject to:

1. Precedence Constraints: For every edge $e_{m,i} \in E$, the start time of v_i on its assigned server x_i must be greater than or equal to the communication finish time of the data from v_m : $\text{ST}(v_i, x_i) \geq \text{FT}_{\text{comm}}(r_{m,i})$ on the link l_{x_m,x_i}

2. Computational Resource Constraints: At any time t on any server s_j, the number of concurrently executing tasks, $n_j(t)$, must not exceed the number of available cores, $n_j^{\max}$.

3. Communication Resource Constraints: At any time t on any link $l_{k,j}$, at most one data transmission can be active.

This formulation accurately captures the complexities of scheduling a DAG-based application within a real-world Vehicular Edge Computing (VEC) environment, providing a foundation for the heuristic and learning-based algorithms proposed to address this challenge

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4 Improved list scheduling for YoloLite DAGs (ILS-YOLO)

To address the makespan minimization problem formulated in chapter 3, we propose a novel scheduling algorithm named Improved List Scheduling for YoloLite DAGs (ILS-YOLO). This algorithm builds upon the well-known HEFT heuristic, enhancing its suitability for the specific resource constraints inherent to the VEC environment [28].

The DAG scheduling problem is formulated as follows:

Objective: Minimize Makespan (X) $= ft_{\text{end}}$, where X is the task-to-server mapping and ft_{end} is the finish time of the final virtual task.

Subject to:

(1) Precedence Constraints: For each subtask $v_i, st_i \geq \max_{v_m \in \text{pred}(v_i)}(ft_m + t_{comm}(m,i))$, ensuring data dependencies.

(2) Computational Constraints: Each subtask v_i is assigned to exactly one server s_{x_i}, with $ft_i = st_i + t_{\text{calc}}(i, x_i)$.

(3) Communication Constraints: Data transfers respect link bandwidth and contention via the Transfer Scheduling Table."

List scheduling algorithms typically manage individual computing units using dedicated scheduling tables. However, treating multi-core CPUs in edge servers as independent computing units with separate scheduling tables can lead to resource fragmentation, where contiguous computational resources remain underutilized over time. As illustrated in Fig. 3(a), a subtask arriving at time would be scheduled on computing unit 1 via insertion scheduling, even though the server has sufficient idle cores overall. This fragmentation arises from the disjoint management of cores, preventing holistic utilization of available resources. The ILS-YOLO algorithm operates in the following main stages: (1) Task Prioritization: Subtasks are sorted based on upward rank values to identify critical paths. (2) Processor Selection: For each subtask, calculate Earliest Ready Time (ERT) from data dependencies, Earliest Start Time (EST) from server availability, and Earliest Finish Time (EFT) to select the optimal server. (3) Resource Allocation and Offloading: Assign the subtask to the selected server and update the Unified Scheduling Table for computation and Transfer Scheduling Table for communication. (4) Iteration: Repeat until all subtasks are scheduled, minimizing overall makespan.

Additionally, static scheduling often assumes fixed communication costs and contention-free links, which contradicts real-world scenarios with limited channel capacity. In practice, data transfers on the same communication link compete for resources, necessitating a queuing model. Here, we model each link as a single-server queue (first-in-first-out, FIFO), where only one subtask can be transmitted at a time, and others must wait in the queue. During processor selection, ignoring queuing delays and allocation impacts on link schedules can severely degrade task completion times and system performance.

To address these issues, we enhance list scheduling with two key improvements:

(1) Unified Scheduling Table: Centralizes the management of all cores on a server to coordinate resource allocation. By tracking the total number of busy cores at each time slot, this table enables holistic scheduling, avoiding fragmentation and ensuring contiguous resource utilization.
(2) Transfer Scheduling Table: Explicitly records transmission schedules on communication links to account for queuing delays. This allows accurate calculation of communication latencies by incorporating both data transmission time and link availability.
As depicted in Fig. 3(b), the unified scheduling approach not only tracks assigned subtasks but also monitors real-time core availability, ensuring efficient resource utilization and reducing makespan.

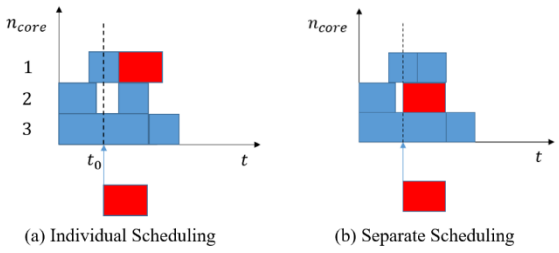


Figure 3: Example diagram of resource fragmentation

The first phase of the ILS-YOLO algorithm is task prioritization, which remains consistent with the HEFT algorithm. We compute an upward rank, rank_up (v_i), for each subtask v_i to estimate its priority. The upward rank represents the length of the critical path from v_i to the exit node v_{end} and is calculated recursively starting from the exit node:

$$\text{rank_up}(v_i) = \overline{t_i^{\text{calc}}} + \max_{v_j \in \text{succ}(v_i)} \left(\overline{c_{i,j}} + \text{rank_up}(v_j)\right) \quad (10)$$

Here, $t_{\text{calc}}(i)$ represents the average computation time of subtask v_i across all servers, computed as the mean of $t_{\text{calc}}(i,s)$ for all $s \in S$. Similarly, $c_{i,j}$ is the average communication time for data from v_i to v_j, ensuring hardware-agnostic task prioritization before processor-specific scheduling. The recursion base case is rank_up $(v_{\text{end}}) = t_{\text{end}}^{\text{calc}} = 0$. After computing the ranks for all tasks, they are sorted into a prioritized list in descending order of their rank values.
In the processor selection phase, the algorithm iterates through the prioritized list. For each subtask v_i, it evaluates the Earliest Finish Time (EFT) on every possible server $s_j \in S$. The subtask is assigned to the server yielding the minimum EFT. To calculate a realistic EFT, our algorithm leverages detailed latency models that incorporate both the Unified Scheduling Table for computation and the Transfer Scheduling Table for communication.
For each pair (v_i, s_j), the Earliest Ready Time $\left(\text{ERT}(v_i, s_j)\right)$ is determined by consulting the Transfer Scheduling Tables for all incoming data links to server s_j, providing a realistic estimate of when all prerequisite data will arrive. Next, using the Unified Scheduling Table for server s_j, the algorithm identifies the earliest available time slot that accommodates v_i 's computation requirements. This time marks the Earliest Start Time ($\text{EST}(v_i, s_j)$). The EFT is then calculated as:

$$\text{EFT}(v_i, s_j) = \text{EST}(v_i, s_j) + t_{i,j}^{\text{calc}} \quad (11)$$

After evaluating all servers, v_i is scheduled on the server s_{j^*} that minimizes its EFT. The scheduling tables are updated to reflect this allocation.
An example of the ERT calculation is shown in Fig.4. Consider subtasks v_3, v_4, v_5 as predecessors of v_6, with servers s_1, s_2, s_3. Subtask v_3 completes on s_1 and transmits results to s_3 via link l_{13}. Subtask v_4 completes on s_2 and transmits results to s_3 via link l_{23}. Subtask v_5 also completes on s_2 and transmits results to s_3 via link l_{23}. Since the transmission of r_{46} is not yet complete, r_{56} must wait for r_{46} to finish before it can start. The earliest ready time for v_6 is determined by the completion time of r_{56}.

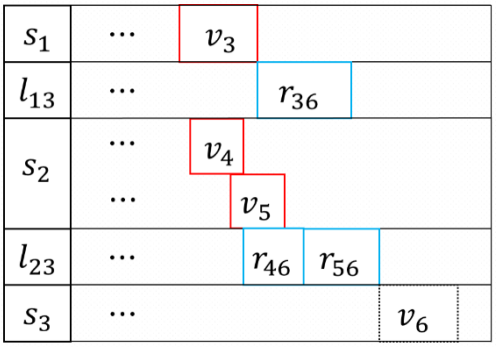


Figure 4: Example of the ERT calculation

The pseudocode for the ILS-YOLO algorithm is provided below:

Algorithm 1: ILS-YOLO Algorithm

Input: Task DAG *G=(V,E)*, set of computing resources *S*, communication overhead matrix *C*, computation overhead matrix *W*, list scheduling algorithm *alg*

Output: Server allocation for each subtask and corresponding start times to minimize makespan

1. Sort subtasks: Prioritize subtasks based on the ranking strategy of algorithm alg.
2. Initialize decision queue: Create an empty decision queue and insert the start subtask into the queue.
3. While the queue is not empty:

   Select subtask: Remove the highest-priority subtask v_i from the queue.

   For each server $s_j \in S$:

   Calculate ERT: Using the transfer scheduling table, determine the earliest time when all predecessor data for v_i will arrive at s_j.

   Determine EST: Based on ERT and server s_j 's unified scheduling table, find the earliest available time slot.

   Calculate EFT: Compute the earliest finish time for v_i on s_j.

4. Allocate subtask: Assign v_i to the server s_j that yields the minimum EFT according to alg's assignment strategy.
5. Update decision queue: Reflect the new resource allocation in the scheduling tables and update the decision queue.
6. End While

5 Performance evaluation

This section evaluates the performance of the proposed Improved List Scheduling for YoloLite DAGs (ILS-YOLO) algorithm through simulation experiments, focusing on its efficiency in task offloading and scheduling within vehicular edge computing (VEC) environments. This evaluation is designed not only to benchmark ILS-YOLO against established scheduling heuristics but also to rigorously test its robustness under adverse and varying network conditions, a critical aspect for real-world VEC deployments. Our comparative analysis also considers recent advancements in task offloading, as contextualized in our literature review, to validate the novelty and effectiveness of our approach. Both offline and online scenarios are considered to validate the algorithm's robustness under different conditions.

5.1 Experimental setup

In offline scenarios, we analyze the algorithm's performance on individual tasks without dynamic task arrivals, using Python-based simulations to isolate the effects of resource allocation and scheduling strategies. The simulation framework includes four modules: parameter configuration, DAG task generation, scenario construction, and scheduling execution, with key parameters listed in Table 3. The Bandwidth factor (Bw factor) scales the baseline link bandwidths (Table 3) to simulate varying network conditions. For instance, a Bw factor of 10^{-1} reduces the bandwidth to 10% of its default value, testing the algorithm's robustness under constrained communication.

Table 3: Simulation parameters

Parameter	Value
Edge server CPU frequency (f_e)	2 GHz
Cloud server CPU frequency (f_c)	4 GHz
Edge server CPU cores ($n_e^{\max}$)	1
Cloud server CPU cores ($n_c^{\max}$)	3
Edge-edge link bandwidth ($B_{e,e}$)	83 MHz
Edge-cloud link bandwidth ($B_{e,c}$)	17 MHz
Edge server transmit power (p_e^{trans})	0.5 W
Cloud server transmit power (p_c^{trans})	1.2 W
Channel gain (g)	-40 dB
White noise power (N_0)	10^{-6} W
Maximum computation ($w_{\max}$)	2×10^8 cycles

DAG tasks are generated with random structures to cover diverse workloads, as outlined in Table 4. The key parameters include node count (n), maximum out-degree, depth coefficient (α), regularity (β), and communication-to-computation ratio (CCR). The CCR (defined as $r_{\max}/w_{\max}$) characterizes task types, where lower CCR indicates computation-intensive tasks.

Table 4: DAG generation parameters

Parameter	Value
Node count (n)	[20, 30, 40, 50, 100, 200]
Maximum out-degree	[1, 2, 3, 4, 5]
Depth coefficient (α)	[0.5, 1.0, 2.0]
Regularity (β)	[0.0, 0.5, 1.0]
CCR	[0.005, 0.025, 0.05, 0.25]

The performance metric speedup is defined as the ratio of sequential execution time (seq) to makespan, where $seq = \min \sum_{i=1}^{n} t_{i,j}^{\text{calc}}$ represents the optimal single-processor execution time.

5.2. Impact of transfer scheduling table

To assess the role of communication resource management, we vary the initial link bandwidth and compare task completion times with and without the transfer scheduling table. As shown in Fig.5, reducing bandwidth increases makespan, highlighting the criticality of realistic communication modeling. Fig.6 demonstrates that the ILS-YOLO algorithm with a transfer scheduling table achieves an average 40% reduction in makespan compared to baseline methods, confirming that explicit modeling of link contention significantly improves communication efficiency and reduces latency.

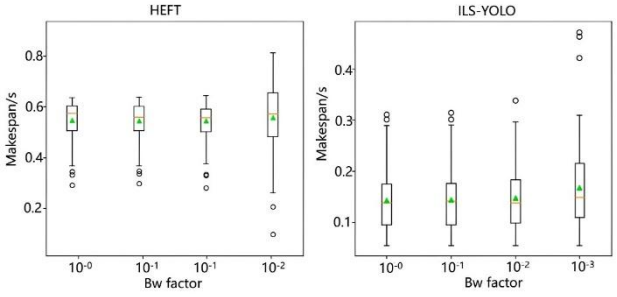
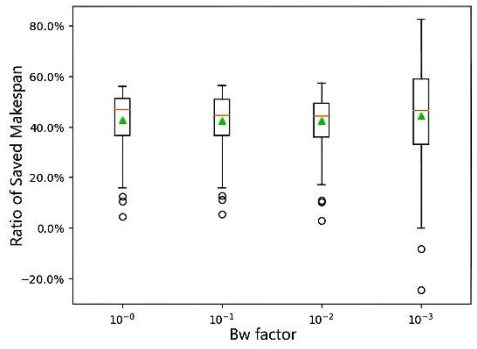


Figure 5: Comparison of task completion times under different bandwidths



Firure 6: Comparison of task completion time saving rates under different bandwidths

5.3 Field real-time vehicle detection system experiment

The experiment begins with preprocessing and analyzing a massive dataset of driving trajectories. First, the overall data is sorted and partitioned by vehicle ID and the time-series information of trajectory points to derive the trajectory path of each vehicle. Second, road intersections are divided by geographical regions, and vehicle trajectory paths passing through each intersection are extracted to reconstruct the overall vehicle flow status at each intersection. As shown in Fig. 7, the horizontal axis represents longitude and the vertical axis represents latitude. By mapping vehicle trajectory points to the map using latitude and longitude values, the real-time driving positions and trajectory status of vehicles can be obtained. Analyzing the road network information and all vehicle trajectory points further reveals vehicle trajectories passing through intersection regions at different time points, enabling the identification of traffic flow dynamics at road intersections. Traffic flow variation characteristics at different intersections can be extracted from massive vehicle trajectory data.

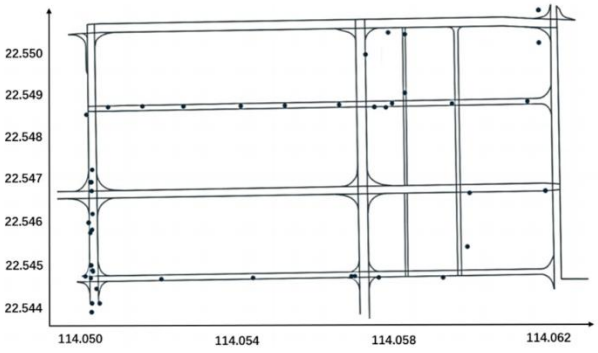


Figure 7: Shenzhen urban road data

The DAG model used in this experiment is based on the principles of PointFusion. PointFusion is a vision-point cloud based 3D object detection algorithm, whose architecture is shown in Figure 8. First, 3D point cloud features are extracted by PointNet, and RGB image features are extracted by Resnet. Then, the two types of features are further fused, and 3D bounding box corner offsets and position information are extracted by MLP. According to the structure of PointFusion, the computational amount and data volume of each stage are analyzed, and it is abstracted into a field DAG model.

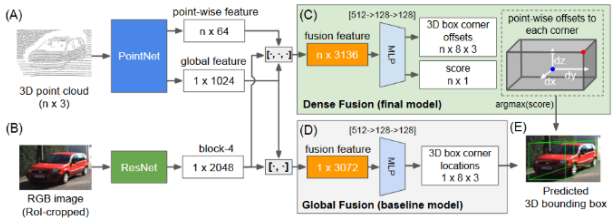


Figure 8: Field real-time DAG model

Our evaluation combines extensive synthetic DAG simulations (Table 4) with diverse structures (node counts, out-degrees, CCRs) to ensure generalizability across application scenarios. The Shenzhen urban road dataset (Figure 7) serves as a real-world anchor, abstracting a complex 3D object detection task (PointFusion, Figure 8) to validate ILS-YOLO's effectiveness in realistic vehicular settings.

(1) We evaluate the following algorithms:.Cloud-only: All tasks are offloaded to the cloud server.

(2) HEFT-singlecore: Standard HEFT without unified core scheduling.

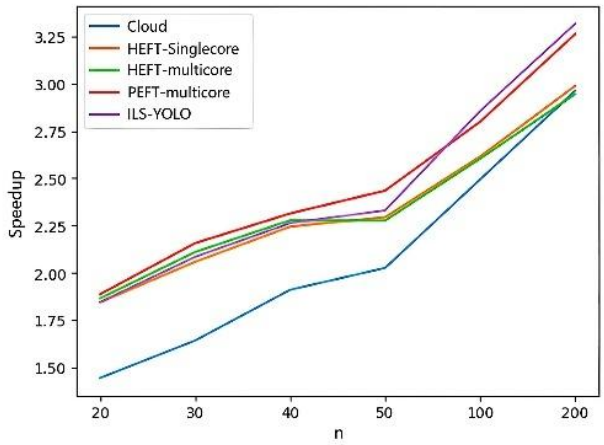
(3) HEFT-multicore: HEFT with unified scheduling of multi-core servers.

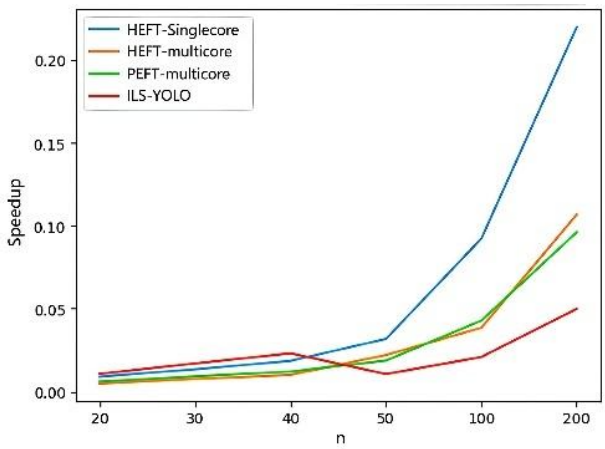
(4) PEFT-multicore: Predictive Earliest Finish Time algorithm with multi-core unification.

(5) ILS-YOLO: The proposed Improved List Scheduling algorithm integrating unified core scheduling and transfer scheduling tables.

Fig.9 compares speedup across algorithms for varying node counts. ILS-YOLO consistently outperforms HEFT-singlecore and Cloud-only, achieving up to 2.5× speedup for large DAGs (n=200), while HEFT-multicore and PEFT-multicore show moderate improvements. The superior performance of ILS-YOLO is attributed to its unified core scheduling, which mitigates resource fragmentation, and transfer scheduling, which optimizes communication utilization. The ILS-YOLO algorithm incurs overheads for calculating ERT, EST, EFT, and updating scheduling tables. These operations, while computationally intensive, are polynomial in complexity, as shown in Figure 9(b), where the algorithm's running time scales efficiently with DAG size, ensuring practicality for real-time vehicle detection.

(a)

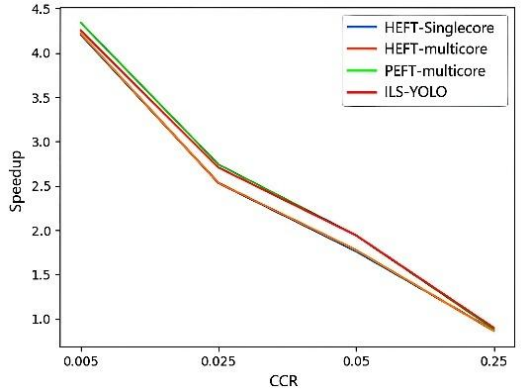




(b)

Figure 9: Comparison of algorithm performance under different numbers of nodes, (a) trend of speedup with the number of nodes, (b) trend of algorithm running time with the number of nodes

Fig. 10 illustrates makespan under different CCR values. For computation-intensive tasks (CCR=0.005), ILS-YOLO reduces makespan by 35–50% compared to HEFT-singlecore, as offloading to edge/cloud servers leverages parallel computation. For communication-intensive tasks (CCR=0.25), the gain narrows to 15–25%, reflecting the increased impact of link latency, but ILS-YOLO still outperforms baselines due to its queuing-aware communication model.



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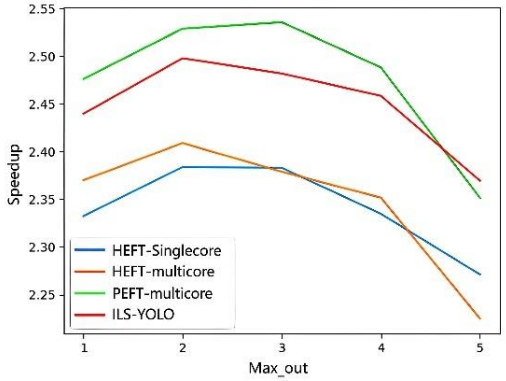
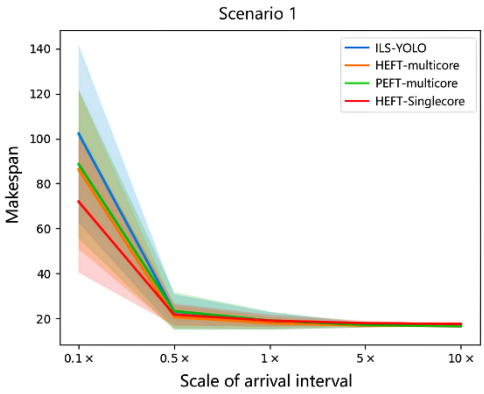


(b)

Figure 10: Comparison of algorithm performance under different CCR and maximum out-degree, (a) trend of speedup with CCR, (b) trend of speedup with maximum out-degree

In the online scenario, tasks are generated continuously, requiring the algorithm to make real-time offloading decisions for new tasks. This setup evaluates the algorithm's capability to handle continuous task streams. The DAG task data used in this experiment is derived from scientific workflow datasets commonly employed in related research, including Scenerios1-2. When the task inter-arrival time is small (high load), the average task completion time across all algorithms increases. This is because new tasks must be scheduled using remaining resources while old tasks are still being processed, impacting completion times. As the inter-arrival time increases (tasks become sparser), completion times decrease gradually, as new tasks can utilize more available resources, approaching the performance of offline scheduling. Figure 11 demonstrates ILS-YOLO's scalability in handling concurrent task arrivals under high load, maintaining performance advantages over baselines. In the online scenario, tasks arrive continuously, testing ILS-YOLO's real-time scheduling capability. Scenario 1 uses a scientific workflow dataset with a computation-intensive DAG (low CCR, high node count), while Scenario 2 employs a communication-intensive DAG (high CCR, dense edges). Figure 11 shows that under high load (small task inter-arrival times), makespan increases across all algorithms due to resource contention, as new tasks compete for limited server cores and bandwidth. ILS-YOLO outperforms baselines by leveraging the Unified and Transfer Scheduling Tables to mitigate contention, achieving lower makespan. As inter-arrival times increase, performance approaches offline scheduling, with ILS-YOLO maintaining a consistent advantage.



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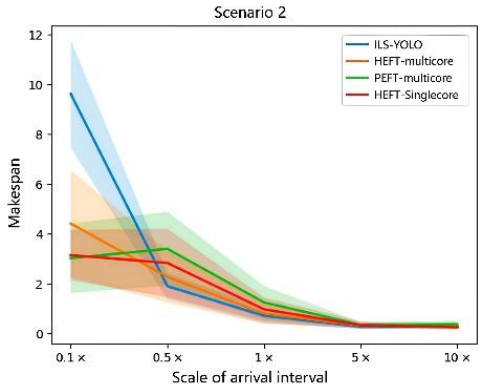

(b)

Figure 11: Makespan under different scenarios

A critical requirement for any scheduling algorithm intended for real-time systems is its ability to scale efficiently with the problem size. To address the reviewer's concern about scalability to more vehicles, tasks, and servers, we provide both a theoretical complexity analysis and an empirical validation of ILS-YOLO.

Theoretically, the computational complexity of the ILSYOLO algorithm is dominated by its two main phases. The first phase, task prioritization via upward rank calculation, involves a traversal of the DAG, which has a complexity of $O(n + e)$, where n is the number of subtasks and e is the number of dependencies (edges). The second phase, processor selection, iterates through each of the n tasks in the prioritized list. For each task, it evaluates the Earliest Finish Time (EFT) on all p available servers. This calculation requires checking the data arrival times from all predecessor tasks. In the worst case, this results in a complexity of O(n * p * dmax), where dmax is the maximum in-degree of any node in the DAG. Therefore, the overall time complexity of ILS-YOLO is polynomial, ensuring that its running time does not grow exponentially as the number of tasks or servers increases.

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However, we acknowledge that the current heuristic-based approach is not inherently adaptive to real-time, unpredictable changes in network state or server availability. While our online scenario experiments (Figure 11) demonstrate robustness to continuous task arrivals, developing a truly adaptive scheduling mechanism, perhaps by integrating reinforcement learning to dynamically adjust scheduling policies, remains a critical direction for future work to enhance generalization in highly stochastic VEC environments.

6 Conclusion

This paper has presented an innovative solution to enhance real-time vehicle detection in vehicular edge computing environments through the development of the Improved List Scheduling for YoloLite DAGs (ILS-YOLO) algorithm. The ILS-YOLO algorithm specifically addresses the challenge of minimizing end-to-end detection latency for the YoloLite pipeline, which is modeled as a Directed Acyclic Graph (DAG) to capture the dependencies and workload characteristics of the inference process. By introducing a Unified Scheduling Table and a Transfer Scheduling Table, the algorithm effectively mitigates resource fragmentation on multi-core servers and accurately models communication overhead, leading to obvious improvements in resource utilization and scheduling efficiency. The ILS-YOLO algorithm is scalable for large-scale networks, with polynomial complexity enabling efficient handling of many servers and requesters, as validated by simulations with DAGs up to 200 nodes (Section IV). Its focus on minimizing makespan through accurate resource and communication modeling makes it ideal for delay-sensitive applications like real-time vehicle detection, achieving up to 2.5× speedup over baselines, ensuring low-latency performance in intelligent transportation systems. These findings underscore the practical advantages of ILS-YOLO in supporting the demanding requirements of intelligent transportation systems and autonomous driving applications where low latency and high accuracy are paramount.

The proposed ILS-YOLO algorithm represents a substantial advancement in the field of vehicular edge computing for real-time AI applications. Its detailed consideration of both computational and communication constraints within the VEC environment ensures that it can dynamically adapt to the resource limitations and varying workloads typical of

vehicular networks. Future work will integrate dynamic vehicle mobility patterns, RSU handoffs, and fluctuating wireless conditions into the ILS-YOLO framework. This will enhance its applicability to real-world VEC deployments, building on the current model's focus on optimized DAG scheduling.

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EEG Signal Classification for Motor Imagery Tasks Using a Deep Stacking Network Optimized by Particle Swarm Optimization

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Keywords: EEG signal processing, PSO, deep stacked neural network, motor imagery, brain-computer interface

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This research proposes a Deep Stacked Network (DSN) model optimized with a particle swarm optimization (PSO) algorithm for classifying electroencephalogram (EEG) signals in motor imagery tasks. Experiments based on the BCI Competition II dataset confirm the effectiveness of the proposed method, which achieves an accuracy of up to 89.42% and outperforms traditional deep models such as DNN and DBN. The study demonstrates that the combination of DSN and PSO enables robust and accurate recognition of brain states, which is important for brain-computer interface devices.

Povzetek: Članek predlaga model Deep Stacked Network (DSN), optimiziran z algoritom roja delcev (PSO) za klasifikacijo signalov elektroencefalograma (EEG) pri nalogah motorične imaginacije.

1 Introduction

As computer technology and signal processing techniques have rapidly developed, an increasing number of scholars have attempted to apply them in the field of neural learning. Electroencephalography (EEG) serves as an important non-invasive method for recording brain activity [1]. By using scalp electrodes, EEG captures the weak electrical signals produced by neuronal activity in the brain, which reflect dynamic changes in the brain under different task-related states. Common EEG rhythms, such as Delta waves, Alpha waves, and Beta waves, are closely associated with states of relaxation and focused attention [2]. Studying the patterns of these signal changes not only helps improve the accuracy of brain-computer interface systems [3] and user experience, but also provides a significant window into understanding brain function mechanisms.

Traditional methods for EEG feature extraction primarily include models such as the AutoRegressive Model (AR), Wavelet Transform, and Common Spatial Pattern (CSP) [4]. These methods extract features from signals in the time domain, frequency domain, or spatial domain through specific algorithms, making them suitable for particular application scenarios. In the classification stage, models such as Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) [5] are widely employed. Although these methods can achieve effective classification of EEG signals to a certain extent, their feature extraction capabilities are limited by predefined algorithm frameworks and struggle to capture complex dynamic characteristics of the signals.

With the rapid development of Deep Learning technology [6], models such as Deep Belief Networks (DBN) [7], Sparse Autoencoders [8], and Convolutional Neural Networks (CNN) [9] have gradually become important tools for EEG signal analysis. These deep learning models, through multi-layered nonlinear transformations, can automatically extract higher-level abstract features from raw EEG signals, significantly improving classification performance. In recent years, various advanced methods related to deep learning have emerged, further propelling the development of EEG signal analysis. For example, Recurrent Neural Networks (RNN) [10], including variants such as Long Short-Term Memory (LSTM) [11] and Gated Recurrent Units (GRU) [12], are used to capture temporal dynamics in EEG signals. These models can handle long-term dependencies, making them particularly suitable for tasks requiring analysis of temporal characteristics. Graph Convolutional Neural Networks (GCN) [13] model inter-channel relationships in EEG signals based on graph structures, making them suitable for analyzing multi-channel EEG data. GCN can process non-Euclidean data, better representing spatial characteristics of EEG signals. Generative Adversarial Networks (GAN) [14] use adversarial training between a generator and a discriminator to generate high-quality EEG signal samples, making them suitable for data augmentation and signal reconstruction tasks. Attention mechanisms [15], combined with Transformer architectures or self-attention mechanisms, dynamically assign importance to different temporal and spatial features, improving the efficiency and accuracy of feature extraction.

Compared to traditional techniques, these deep learning methods not only have significant advantages in

feature extraction and classification performance, but also reduce manual intervention through end-to-end learning models, providing broader research directions for EEG signal analysis. In the future, designing more efficient and robust EEG signal analysis frameworks by combining multiple deep learning technologies will be one of the key research directions in the field [16].

Table 1: Summary of related works on EEG signal classification

Reference	Method	Dataset
[9]	CNN	BCI Competition II
[11]	LSTM	Epileptic EEG
[13]	GCN	SEED (Emotion)
[16]	DNN	BCI Competition IV
This Work	PSO-DSN	BCI Competition II

Table 1 gives a summary of related works on EEG signal classification. In summary, with the continuous progress of deep learning technology, feature extraction and classification techniques for EEG signals will see new breakthroughs. How to further improve model generalization ability and adaptability based on existing methods will be an important challenge for future research.

This paper proposes a new method for EEG signal feature learning based on the Deep Stacking Network (DSN) and further employs Particle Swarm Optimization (PSO) technology to optimize the hidden layer parameters of the DSN model. Through this approach, we aim to achieve accurate identification and classification of EEG signals for motor imagery tasks. The primary objective of this study is to improve the accuracy of EEG signal classification for motor imagery tasks by developing a hybrid model that combines the representational power of Deep Stacking Networks (DSN) with the global optimization capabilities of Particle Swarm Optimization (PSO). We hypothesize that using PSO to optimize the parameters of the DSN's hidden layers will lead to better feature learning and higher classification accuracy compared to standard deep learning models like DNN and DBN. This hypothesis is tested through comparative experiments on publicly available BCI competition datasets.

2 Method introduction

2.1 Brain-computer interface

The disciplines of brain cognitive science and signal processing technology play pivotal roles within the realm of Brain-Computer Interfaces (BCI), particularly in the acquisition, identification, classification, and feedback control of electroencephalogram (EEG) signals. EEG signals, which are recorded through scalp electrodes as subtle electrical manifestations of neuronal activity within the brain, encompass common brainwave patterns reflecting distinct states of consciousness [2]. To enable the control of external devices, including wheelchairs, prosthetics, or computer interactions, EEG signals undergo preprocessing stages such as filtering and denoising. Subsequently, these signals are subjected to feature extraction—employing temporal, spectral, or time-frequency characteristics—followed by classification through machine learning algorithms. The incorporation of a feedback regulation mechanism significantly enhances the performance of BCI systems, allowing for real-time adjustments to dynamically accommodate the fluctuating states of users' conscious awareness, shown as Figure 1. As human brain activity undergoes continuous variations in alignment with changes in consciousness, the study of these underlying principles holds the potential to elevate the precision and user experience of BCI technologies. Moreover, this research offers a crucial vantage point for the deeper comprehension of brain function.

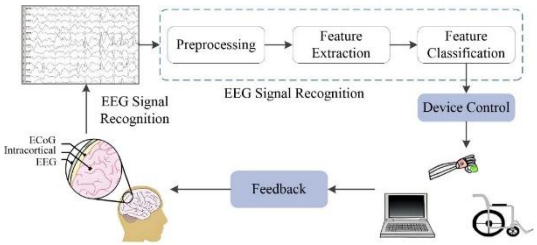

Figure 1: Basic principle of brain-computer interface system.

2.2 Deep stacking networks optimized via PSO

The Deep Stacking Network (DSN), a sophisticated architectural framework, is constituted by the amalgamation of multiple stacked expert layers, each housing a diverse array of experts, which may encompass varied classifiers or regressors. The outputs derived from each expert layer are meticulously amalgamated to produce the final output of the model. Unlike conventional models that rely on predefined parameter structures, DSN adeptly learns the optimal combination and weighting of experts in an adaptive manner based on the data itself. This inherent flexibility endows the model with the capacity to adeptly accommodate disparate data distributions, thereby enhancing its adaptability and performance across a spectrum of datasets [17]. Illustrative representations of the DSN model's intricate structure can be apprehended from Figure 2.

Supposing that each subnet encompasses an input layer, a hidden layer, and an output layer, the output of the hidden layer for the i-th subnet can be articulated as:

$$h_i = f(W_i x + b_i) \tag{1}$$

Herein, x represents the input vector, while W_i signifies the weight matrix mapping from the input layer to the hidden layer. Additionally, b_i denotes the bias vector of the hidden layer, and f stands as the activation function. The ultimate output y_i of the subnetwork can

thus be expressed as

$$y_i = g(U_i h_i + c_i) \tag{2}$$

where, U_i denotes the weight matrix from the hidden layer to the output layer, c_i represents the bias vector of the output layer, and g signifies the activation function of the output layer. The overall output of the deep stacked network is a composite of the outputs from each individual subnetwork, culminating in the ultimate output Y through a weighted summation process.

$$Y = \sum_{i=1}^{n} \alpha_i y_i \tag{3}$$

Among them, α_i represents the weight assigned to the output of the i-th subnetwork, and n signifies the total number of subnetworks. These weights can either be learned through training or predetermined based on empirical insights. It is important to note that this weighted sum combines the final outputs of each module, which are computed in parallel. However, the internal hidden representations are used to enrich the input to subsequent modules.

The loss function during the training process is defined as follows:

$$L = \frac{1}{m} \sum_{j=1}^{m} (Y_j - \hat{Y}_j)^2 \tag{4}$$

Herein, m denotes the quantity of training samples, Y_j represents the actual output of the j th sample, and $\hat{Y}_j$ signifies the network's predicted output. For classification tasks, the cross-entropy loss may be employed.

$$L = -\frac{1}{m} \sum_{j=1}^{m} \sum_{k=1}^{K} y_{jk} \log(\hat{y}_{jk}) \tag{5}$$

Here, K denotes the number of categories, y_{jk} represents the actual label indicating that the j^{th} sample belongs to the k^{th} category, and $\hat{y}_{jk}$ signifies the network's predicted probability that the j^{th} sample belongs to the k^{th} category.

During the training process, the gradient descent algorithm is typically employed to update the network's parameters, with the aim of minimizing the loss function. For the parameter θ, the update formula is

$$\theta = \theta - \eta \frac{\partial L}{\partial \theta} \tag{6}$$

where, η represents the learning rate, which governs the magnitude of each parameter update.

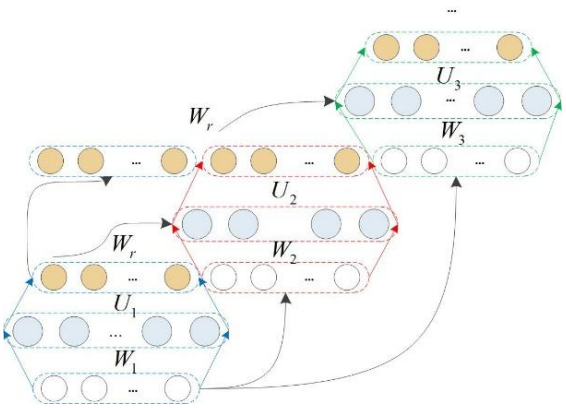

Figure 2: Basic principle of deep stacking networks

This article proposes a deep stacked network comprising two stacked modules, as depicted in Figure 3. The network adopts a modular design consisting of two separately trained modules, each utilizing target outputs for supervised learning. In the design where intermediate hidden layers are partially visible, starting from the second module, a portion of the hidden layer nodes are initialized by replicating the hidden layer nodes trained in the preceding module, and further expanded with a portion of unknown nodes. The hidden layer of each module is initialized using unsupervised pre-training with a Restricted Boltzmann Machine (RBM). This approach increases the complexity and expressive power of the hidden layer [18]. The model regards the hidden layers as intermediate layers rather than final output layers, thereby making the training of hidden layers more flexible. In terms of network architecture, the number of hidden layer nodes increases layer by layer, embodying the concept of partial visibility in hidden layers, which involves inheriting and expanding upon the hidden layers of the previous module. By employing separate training for each module, the computational complexity is equivalent to stacking multiple single-hidden-layer neural networks, thus maintaining flexibility while controlling computational costs.

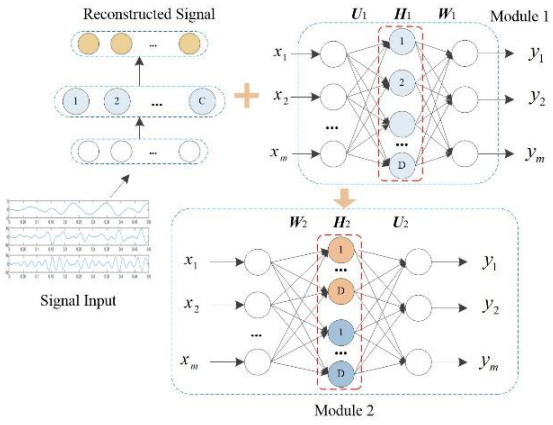

Figure 3: The proposed deep stacked network framework for signal recognition

Particle Swarm Optimization (PSO), as a global optimization algorithm, effectively explores the parameter space of hidden layers, circumventing the local optima issue encountered by traditional gradient descent methods, thereby enhancing the model's generalization capability and predictive performance [19]. The integration of the Particle Swarm Optimization algorithm with the deep stacked network (DSN) for parameter optimization, particularly in the context of visible parameters within hidden layers, represents an innovative approach that marries evolutionary algorithms with deep learning. The primary objective of this methodology is to elevate the performance and generalization capacity of the DSN, leveraging PSO's global search prowess to discover superior parameter configurations, especially where partial visibility of hidden layer parameters is a factor.

The detailed procedure can be observed in Figure 4. Initially, a multi-layered DSN model is constructed, wherein the visible parameters of the hidden layers are encoded into position vectors of PSO particles. Subsequently, the performance metrics of the validation set are defined as the fitness function. By harnessing PSO's global search capabilities, the algorithm iteratively refines the particle positions and velocities until the termination criteria are met.

Within the particle swarm, the update formulae for the particle's velocity and position are as follows:

$$v_i^{(t+1)} = wv_i^{(t)} + c_1 r_1 (p_{best,i} - x_i^{(t)}) + c_2 r_2 (g_{best} - x_i^{(t)}) \quad (7)$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (8)$$

where, $x_i^{(t)}$ and $v_i^{(t)}$ denote the position and velocity of particle i at time step t. c_1 and c_2 represent the learning factors, governing the particle's inclination to move towards its own best position, $p_{\text{best},i}$. r_1 and r_2 are uniformly distributed random numbers between [0,1]. g_{best} signifies the historical best position of the entire population.

The final DSN model exhibiting the highest fitness was selected, and its performance was validated on the test dataset, thereby achieving highly efficient and stable parameter optimization. The fitness function is presented as follows.

$$fitness = \frac{1}{2N} \sum_{i=1}^{N} \sum_{j=1}^{m} (y_{ij} - t_{ij})^2 \quad (9)$$

Herein, N denotes the number of training samples, and m represents the count of output nodes; y_{ij} and t_{ij} respectively signify the actual output value and the target output value of the j-th component of the i-th sample.

All models were implemented using Python 3.8 and the PyTorch framework, running on a workstation with an Intel i7-12700K CPU and an NVIDIA GeForce RTX 3080 GPU.

The PSO-DSN training procedure begins by initializing a DSN with M modules and setting PSO parameters including swarm size, learning factors, and maximum iterations. First, layer-wise unsupervised pre-training is performed for each module's hidden layer using Restricted Boltzmann Machines. Then, the PSO optimization phase commences, where each particle's position vector encodes the concatenated weights and biases of the DSN's hidden layers. During each iteration, particles are evaluated by decoding their positions into DSN parameters, performing forward passes on the training set, and calculating fitness using Mean Squared Error. Particle velocities and positions are updated following standard PSO equations, and this process repeats until reaching the maximum iteration count. Finally, the global best particle's position is decoded into the DSN, followed by a supervised fine-tuning step using gradient descent on the entire training set, before evaluating the optimized model on the held-out test set.

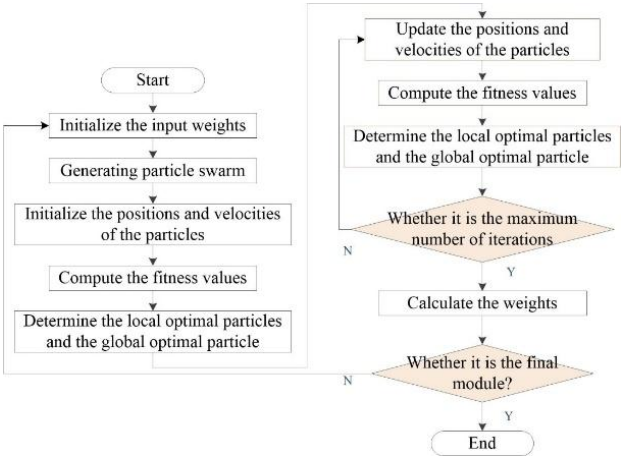

Figure 4: Particle swarm optimization algorithm for parameter optimization

2.3 Deep belief network

Deep Belief Networks (DBNs) [20], a sophisticated deep learning model, are primarily constructed by stacking multiple Restricted Boltzmann Machines (RBMs), as illustrated in Figure 5. For an RBM comprising a visible layer (corresponding to the input layer in Figure 5) and a hidden layer, its energy function is defined as

$$E(v,h) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_{i,j} v_i w_{ij} h_j \quad (10)$$

where, a_i represents the bias of the visible unit i, b_j denotes the bias of the hidden unit j, and w_{ij} signifies the connection weight between the visible unit i and the hidden unit j.

Based on the energy function, the joint probability distribution of the RBM is as follows:

$$P(v,h) = \frac{e^{-E(v,h)}}{Z} \quad (11)$$

$$Z = \sum_{v,h} e^{-E(v,h)} \quad (12)$$

where, the normalization constant Z is referred to as the partition function.

Given the hidden layer, the conditional probability of the visible layer is:

$$P(v_i = 1 \mid h) = \sigma(a_i + \sum_j w_{ij} h_j) \quad (13)$$

Given the visible layer, the conditional probability of the hidden layer is

$$P(h_j = 1 \mid v) = \sigma(b_j + \sum_i v_i w_{ij}) \quad (14)$$

where, σ denotes the sigmoid function.

During the training of deep belief networks, a combined approach is typically employed, integrating layer-wise unsupervised pre-training with supervised fine-tuning. For Restricted Boltzmann Machines (RBMs), the Contrastive Divergence (CD) algorithm is utilized to approximate the gradient calculation, facilitating the updating of weights and biases.

$$\Delta w_{ij} = \alpha([v_i h_j]_{\text{data}} - [v_i h_j]_{\text{recon}}) \quad (15)$$

$$\Delta a_j = \alpha([h_j]_{\text{data}} - [h_j]_{\text{recon}}) \quad (16)$$

$$\Delta b_i = \alpha([v_i]_{\text{data}} - [v_i]_{\text{recon}}) \quad (17)$$

Here, $[]_{\text{data}}$ and $[]_{\text{recon}}$ represent the average probabilities of corresponding unit activations over the real data and reconstructed data, respectively; α denotes the learning rate.

Upon the conclusion of pretraining, the output from the hidden layer of the final RBM is connected to an output layer (e.g., the Output layer), and supervised fine-tuning is performed using the Backpropagation algorithm [21].

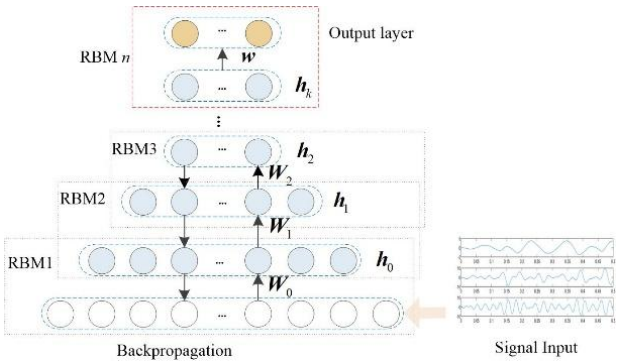

Figure 5: Structure of deep belief network model

3 Experiment and analysis

3.1 Data set and evaluation index

The dataset employed in this experiment is the BCI Competition II Data Set III and IV, which are pivotal components of the second iteration of the Brain-Computer Interface (BCI) Competition. Each of these datasets involves distinct subjects and experimental designs. Data Set III encompasses the EEG recordings of a 25-year-old healthy male, captured using a 118-channel BioSemi ActiveTwo system with a sampling rate of 256 Hz. The experimental tasks involved the imagination of movements of the left hand, right hand, or feet, conducted over two separate sessions on different days. Data Set IV, on the other hand, features the data from a patient suffering from Amyotrophic Lateral Sclerosis (ALS), recorded via a 64-channel EEG system at a sampling rate of 128 Hz. Similar to Data Set III, the experimental tasks in Data Set IV also involved motor imagery, particularly focusing on imagining movements of the left hand, right hand, or feet.

During the experimental process, the raw EEG data underwent preprocessing to mitigate noise and extract salient features. This preprocessing phase involved the application of a band-pass filter to eliminate low-frequency drift and high-frequency noise, segmentation of data into distinct trial segments based on markers, and the removal of electrooculographic (EOG) artifacts and other spurious signals. The experimental framework culminated in the identification and classification of EEG signals through the integration of a Deep Stacking Network (DSN) and Particle Swarm Optimization (PSO). Data were split into 70% training, 15% validation, and 15% test sets. We performed subject-dependent evaluation using 5-fold cross-validation.

3.2 Parameter configuration

When employing Restricted Boltzmann Machines (RBMs) for feature learning, the judicious setting of hyperparameters is pivotal to the model's performance. In this study, the initial values for the learning rate and penalty factor were set at 0.001, incorporating a decay strategy to progressively enhance the model's convergence. The momentum learning rate commenced from a minimal value of 0.0, gradually increasing linearly to 1.0 over 100 epochs, and was further refined through cross-validation to harmonize the model's complexity with its performance. As illustrated in Figure 6, the selected RBM hyperparameters were configured with an initial learning rate of 0.1, a momentum learning rate of 0.6, and a penalty factor of 0.05. Through the judicious arrangement of these parameters, the reconstruction error was mitigated, effectively augmenting the RBM's efficacy in feature learning tasks. Additionally, the parameter settings for the Particle Swarm Optimization algorithm are detailed in Table 2.

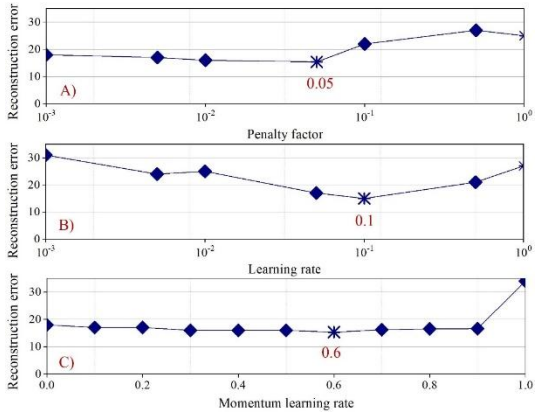

Figure 6: Reconstruction errors of the three RBM parameters

Table 2: Parameter configuration for the particle swarm optimization algorithm

Parameters	Value
Swarm Size	10
Learning Factor	2
Position Range	[-1,1]
Velocity Range	[-0.5,0.5]

The PSO parameters were selected based on a trade-off between computational efficiency and optimization performance. A small swarm size of 10 was chosen to reduce the computational overhead of fitness evaluation, which involves training a DSN module. The standard learning factor value of 2.0 is widely used in the PSO literature [19] to balance the influence of the particle's personal best and the swarm's global best, promoting stable convergence. While larger swarms may offer more exhaustive search, preliminary experiments showed diminishing returns beyond a size of 10 for this specific problem.

3.3 Evaluation of recognition effect

To verify the efficacy of the proposed method, the model was employed in the recognition of brain electrical signals associated with left- and right-hand motor imagery. The number of training samples was varied from 100 to 240 to analyze the model's scalability and data efficiency. As shown in Table 3, with the increase in the number of training samples, the training time progressively extended, in parallel with a rise in recognition accuracy. Specifically, when the training samples increased from 100 to 240, the training time grew from 9.86 seconds to 20.27 seconds, while the recognition accuracy improved from 78.5% (±1.8%) to 89.42% (±1.2%) (results reported as mean ± standard deviation over 5-folds). This phenomenon suggests that a larger volume of training data aids in enhancing the model's generalization capability, thereby achieving a higher recognition accuracy, although it concurrently results in an extended training duration.

Moreover, the data illustrates that with the augmentation of sample numbers, the margin by which accuracy improves gradually diminishes. For instance, the accuracy increased by approximately 4.09% when the samples grew from 100 to 130; yet, from 210 to 240 samples, the improvement was merely around 1.39%. This may indicate the existence of a saturation point, beyond which additional training samples contribute less significantly to accuracy enhancement.

Additionally, taking into account the unique nature of electroencephalogram (EEG) data, such as signal non-stationarity and individual variability, utilizing a larger number of training samples facilitates the model in more effectively capturing these characteristics, thus enhancing its robustness. However, an excessively prolonged training time could constrain the model's applicability in real-time scenarios. To provide a more detailed performance analysis, class-wise precision, recall, and F1-score were calculated for the best-performing model (5 modules, 240 samples). The model achieved an average F1-score of 0.89, with scores of 0.90 for 'Left Hand' imagery and 0.88 for 'Right Hand' imagery, indicating balanced performance across the two classes.

Table 3: Impact of training samples on recognition accuracy and training time

Samples	Training Time (s)	Accuracy (%)
100	9.86	78.5 ± 1.8
130	10.14	83.51 ± 1.5
160	12.50	85.09 ± 1.4
190	17.93	87.67 ± 1.3
210	18.84	88.03 ± 1.3
240	20.27	89.42 ± 1.2

3.4 Comparative experiment

This study applies the PSO-optimized hidden layer parameter approach to the DNN, DBN, and DSN deep learning models, conducting comparative experiments. Four subjects, namely S1-4, were selected from the dataset. Figure 7 illustrates the disparity in the motor imagery recognition performance of these models across the subjects. To ensure a fair comparison, all baseline models were configured with standard settings: DNN used a single hidden layer (256 units) with the Adam optimizer; DBN employed a two-layer RBM structure (256-128 units) with backpropagation fine-tuning; DSN adopted a two-module architecture (128-256 nodes) incorporating RBM pre-training; and PSO-DSN enhanced the DSN with PSO optimization.

According to Figure 7, as the number of stacked modules increases, the models exhibit distinct trends in recognition accuracy, closely related to their respective characteristics. The DNN model demonstrated relatively

inferior performance in this experiment, particularly under a high number of stacked modules, where the improvement in recognition accuracy was minimal. Therefore, the DNN is more suitable for handling simpler tasks or datasets with more distinct features. Secondly, the DBN model showcased a more stable performance in this experiment, with a notably significant increase in recognition accuracy at moderate numbers of stacked modules. However, as the number of stacked modules grows, the improvement in the DBN's recognition accuracy diminishes gradually, indicating potential issues of overfitting and increased training complexity at higher module counts.

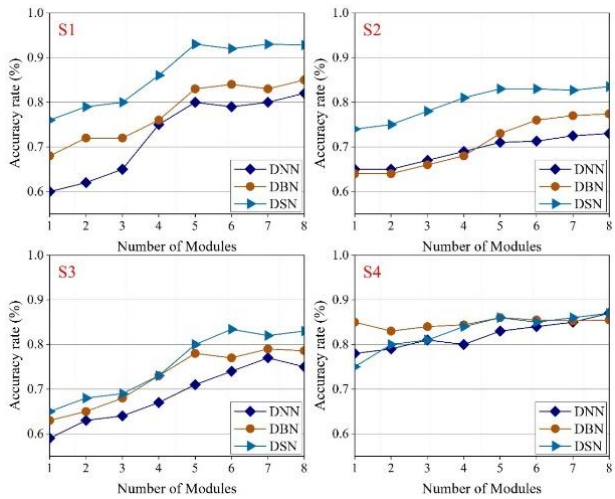

Figure 7: Recognition accuracy of various deep learning models across four subjects

The DSN model demonstrated superior performance in this experiment, particularly under configurations with a higher number of stacked modules, where its recognition accuracy significantly surpassed that of the DNN and DBN models. A key feature of the DSN model is the incorporation of a supervised learning mechanism, which optimizes model parameters through layer-wise supervised training, thereby enhancing its ability to capture intricate patterns in the data. This advantage renders the DSN model particularly effective in handling complex tasks, such as EEG signal recognition, especially when the number of modules is high, leading to a notable increase in recognition accuracy. Additionally, the DSN model exhibits greater stability under high module counts, indicating a robust resistance to overfitting. Consequently, the DSN model is better suited for tasks demanding high precision and complexity.

Experimental data suggests that 4-5 stacked modules represent the optimal configuration for most models, with the DSN model achieving peak recognition accuracy at 5 modules. As the number of stacked modules increases, the overall recognition accuracy tends to rise, though the rate of improvement diminishes, signaling the presence of a saturation point. Beyond this point, additional stacked modules contribute marginally to accuracy enhancement while significantly increasing training time and computational complexity. Therefore, in practical applications, the selection of an appropriate number of stacked modules necessitates a balance between recognition accuracy and computational resources. Moreover, an increase in the number of stacked modules substantially elevates model complexity, leading to longer training and inference times. This could pose challenges for tasks requiring real-time performance, such as real-time control in brain-computer interfaces. Thus, while models with a higher number of stacked modules offer superior recognition accuracy, their practical implementation must account for real-time performance requirements.

4 Discussion

This study proposed a PSO-optimized DSN model for EEG signal classification. The results demonstrate that our method achieves a competitive accuracy of 89.42% on the BCI Competition II Dataset III, which compares favorably with state-of-the-art methods such as CNNs, LSTMs, and GCNs reported in the literature for similar motor imagery tasks [9,11,13].

The superior performance of the DSN model, particularly with a higher number of stacked modules, can be attributed to two main factors. First, the layer-wise supervised training mechanism allows each module to learn discriminative features directly relevant to the classification task, mitigating the vanishing gradient problem common in very deep networks. Second, the integration of PSO provides a global search strategy for optimizing the visible parameters of the hidden layers, helping the model escape local optima that might trap gradient-based methods. This is especially beneficial for the DSN architecture, where the interaction between modules can create a complex optimization landscape.

However, this performance comes at a computational cost. As shown in Table 3, training time increases with more samples and modules. While PSO-DSN was more accurate than DBN and DNN, its training time was longer due to the PSO iteration process. This presents a trade-off between accuracy and computational efficiency, which must be considered for real-time BCI applications. Future work could focus on developing more efficient hybrid optimization strategies.

A limitation of this study is the use of a relatively small swarm size in PSO. While it was chosen for computational tractability, exploring adaptive swarm sizes or other meta-heuristic algorithms could yield further improvements. Furthermore, the study focused on subject-dependent analysis; evaluating the model's cross-subject generalization capability remains an important area for future research.

5 Conclusion

This paper introduces a method for EEG-based motor imagery classification, based on a neural network optimized by Particle Swarm Optimization. This model integrates the deep network architecture of DSN with the PSO optimization algorithm, combining unsupervised learning with supervised training to enhance the model's capability in extracting features from EEG signals. The study demonstrates that, through a layer-wise learning mechanism, it effectively captures high-order features of EEG signals, laying a solid foundation for precise identification and classification. Comparative analysis reveals that the DSN model outperforms other models in tasks related to EEG signal recognition, particularly when using a higher number of stacked modules, where its recognition accuracy significantly surpasses that of DNN and DBN. The supervised learning mechanism of the DSN model enables it to better grasp complex characteristics of the data, exhibiting strong resistance to overfitting. However, as the number of stacked modules increases, the model's training time and complexity rise significantly, necessitating a balance between recognition accuracy and computational resources. Future research could focus on optimizing the structure and training methods of the DSN model to enhance its performance and efficiency in practical applications, including exploring its cross-subject robustness and applicability to other EEG paradigms. Overall, this approach offers new opportunities for EEG signal analysis and holds great potential for deep application and expansion in fields such as brain-computer interfaces, continuously propelling interdisciplinary research between neuroscience and engineering technology to new heights.

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Deep Learning-Based Restoration of Historic Building Images with Blockchain-Driven Maintenance Data Management

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Ancient buildings, steeped in millennia of human history, stand as precious legacies requiring meticulous preservation and restoration. With this premise, this study proposes a restoration method for damaged ancient structures based on a deep neural network. A curated dataset of ancient building images — including diverse damage patterns and material textures-was established to train and validate the model, ensuring robustness across varied architectural styles. The core network architecture is an enhanced U-Net, in which all convolutional layers are replaced with partial convolution layers. The sliding window of partial convolutional layers exclusively performs convolution operations in the relevant region of the image, enabling accurate prediction of building structures with irregular apertures. To further enhance feature extraction and generalization, a dual-transfer learning mechanism is introduced: structural features learned from large-scale architectural datasets are transferred to fine-tune restoration on heritage-specific samples. Consequently, the semantic richness of restoration results is reconstructed. Simultaneously, in accordance with the functional requisites of the ancient building maintenance data storage and sharing system, a dedicated blockchain-driven data storage platform is designed. This platform caters to diverse stakeholders, including lay users, professional restorers, museums, and governmental bodies. The platform employs Hyperledger Fabric technology and a traditional database to ensure secure and reliable data management. Model performance is quantitatively assessed using standard image restoration metrics—Learned Perceptual Image Patch Similarity (LPIPS = 0.725), Peak Signal-to-Noise Ratio (PSNR = 26.16), and Structural Similarity Index Measure (SSIM = 0.57)—demonstrating competitive reconstruction quality. It is worth noting that the proposed building restoration method demonstrates significant potential for cost savings, while also achieving a 25% improvement in efficiency. This potential is particularly relevant within the context of restoring old buildings.

Povzetek: Študija razvije globokonevronski model z izboljšano U-Net arhitekturo in blockchain podporo, ki omogoča natančnejšo ter do 25 % učinkovitejšo obnovo poškodovanih starodavnih stavb.

1 Introduction

Historic buildings serve as indispensable symbols of human history and civilization, capturing the abundant heritage of human endeavor. In the case of China, these structures surpass their intended purpose as preservers of traditional culture, instead embodying the essence of spiritual pillars for cities with precious artistic and scientific values [1, 2]. The preservation of historic buildings has gained increasing global attention. The protection procedures in China have evolved over several decades through the assimilation of foreign experience in protection and the gradual development of a deeper comprehension of cultural heritage. Awareness and competence in heritage conservation have continuously augmented. Motivated by methods and guidelines proposed in [Zhong Ban Fa (2018) No.54] by the General Office of the State Council, People's Republic of China, there has been a growing emphasis on leveraging the potential of big data, the Internet, cloud computing, and other technical resources to fortify scientific and technological support [3]. Information technology, represented by artificial intelligence, has engendered novel avenues for presenting and exploiting cultural heritages, fostering innovation through integrating different elements. Nowadays, heritage preservation has seen continuous promotion. However, the progress of time requires a shift from traditional conservation methods to a more structured, scientific, and comprehensive approach to managing heritage information. This evolution encompasses in-depth excavation, analysis, and an all-encompassing display of heritage value, culminating in dynamic monitoring and early warning of both the heritage sites and their surrounding environment. This phenomenon illustrates the transformation from a reactive approach focused on rescue protection to a proactive and systematic approach centered on preventive conservation, emphasizing the urgent need for enhanced preservation and management of cultural heritage. In the field of

historic building restoration, the convergence of the construction industry with digital technology has led to a surge of digital works in architectural domains. In the current context, the protection of digital property rights has become a pressing problem [4-6].

Numerous authors have conducted notable investigations in architectural heritage conservation, contributing significantly to the discipline. Fadli and Al Saeed (2019) [7] explored Qatar's existing urban conservation strategies, architectural heritage, and modern digitization and archival principles. They aimed to establish a sustainable and interactive archival platform, namely an information modeling platform, for historic buildings in Qatar. Müller et al. (2025) [8] proposed depth inpainting under perspective occlusion environments. If the mask M_0 is provided by user input or through object detection and segmentation, the object can be removed via the inpainting process. This alignment was observed through the establishment of a two-tier database according to Midas standards. Masciotta et al. (2021) [9] explored the significant role of digitization in heritage conservation, drawing insights from several programs focused on the monitoring and preventative protection of historical and cultural heritage. Their endeavor cultivated an integrated and technologically advanced approach, enhancing the process of documenting historical structures and encouraging the active participation of property owners in the preservation and restoration efforts. The defects found in ancient house murals were examined by Li (2021) [10], who identified their origins in both natural and manmade sources. The research improved existing approaches for restoring damaged murals by employing a multifaceted approach involving fracture identification, texture-plane segmentation, and the application of the discrete difference algorithm. Wang and Zhao (2022) [11] advocated the application of 3D images and Virtual Reality (VR) technologies in art, design, and the digital preservation and restoration of ancient buildings. Their work focused on an integrated system for restoring ancient buildings, which incorporated the use of 3D stereoscopy and VR. This technology holds substantial potential for wider implementation in art and design domains. Siountri et al. (2020) [12] underscored the transformative impact of Building Information Modeling (BIM) technology. However, the interplay of Internet of Things (IoT) devices and interconnections between mobile components and stakeholders in a modular environment have given rise to security concerns. The study examined the integration of the application of IoT and blockchain technologies in the construction industry, highlighting their cohesiveness and interoperability within the system architecture and emphasizing building applications. Nawari and Ravindran (2019) [13] explored the increasing adoption and impact of blockchain technology, lauded for its pervasiveness across diverse industries in both public and private sectors. Their study examined how blockchain technology could impact the construction and engineering sectors, evaluating its potential in addressing post-disaster reconstruction challenges. Dey et al. (2023) [14] employed machine learning techniques to segment building roofs using airborne light detection and range (LiDAR) point cloud data. They aimed to enhance the efficiency of LiDAR data processing through machine learning, facilitating automatic identification and segmentation of building roofs. They introduced a novel approach with applications in the remote sensing domain. Gharineiat et al. (2022) [15] comprehensively reviewed automated methods using machine learning for terrain and surface feature recognition in LiDAR data. The study summarized recent research outcomes, focusing on the application of machine learning techniques in LiDAR data processing, providing valuable insights for geography and remote sensing. Mirzaei et al. (2022) [16] thoroughly reviewed machine learning-based 3D point cloud data processing in architecture and infrastructure applications. The research reviewed the applications of machine learning techniques in architecture and infrastructure, emphasizing their significance in data processing and applications, offering profound insights into the field of engineering informatics. Khan et al. (2023) [17] introduced a deep learning framework for extracting building outlines from aerial images. The authors utilized an encoder-decoder structure to achieve building outline extraction through deep learning technology, aiming to enhance the efficiency and accuracy of this process in remote sensing image processing. Vacchio and Bifulco (2022) [18] explored the application of blockchain technology in the cultural heritage domain, providing a comprehensive literature review of its potential value and challenges. The authors summarized the role of blockchain technology in existing research concerning digital reconstruction, cultural heritage preservation, and digitalization of cultural heritage. However, the study did not delve into a detailed analysis of the methods and outcomes of the existing research. Trček (2022) [19] summarized the opportunities and challenges of blockchain technology in heritage preservation. The author emphasized the potential uses of blockchain technology, including cultural heritage digital reconstruction, data protection, and traceability. While the literature offers some practical cases showcasing the application of blockchain technology in cultural heritage preservation, it does not provide detailed technical details or specific operational methods. Although the above research has made significant progress in the field of architectural heritage protection, overall, the existing deep learning and blockchain frameworks still have limitations in meeting the three requirements of "multi-stakeholder

collaboration, security assurance and low-latency transmission".

At the same time, the introduction of blockchain technology is not only for the secure storage and sharing of data, but also for its ability to address the issues of trust and traceability in the maintenance data of historical buildings, especially in multi-party participation, long-term management, and cross-institutional collaboration. Traditional databases find it hard to ensure the true origin and non-tamperability of data. In contrast, the decentralized and tamper-proof mechanisms of blockchain can ensure the transparency and credibility of the data flow process, thus establishing a long-term basis of trust for the protection of architectural heritage. Therefore, this study fills the gaps in previous research concerning the application of deep learning and blockchain technology, offering new techniques and methods for protecting and maintaining historical buildings, holding both academic and practical significance.

2 Design of building restoration model(U-Net and the improved U-Net)

The U-Net is a classical Convolutional Neural Network (CNN) introduced at the 2015 conference. Since its inception, extensive discourse among researchers about its network architecture has led to numerous studies focusing on enhancing the U-Net structure. The U-Net architecture features a symmetrical U-shaped configuration comprising contracting and expanding paths. The contracting path embodies a conventional CNN design with a repetitive structure involving two convolutional operations and a pooling operation in each iteration. The convolutional layer utilizes a uniform kernel size of 3×3, applies the Rectified Linear Unit (ReLU) for activation functions, and incorporates maximum pooling. After each down-sampling operation, the number of feature maps is doubled. In contrast, each stage within the expanding path begins with up-sampling, resulting in a reduction of the number of feature maps by half while doubling their dimensions. Simultaneously, the outcome is superimposed with the appropriate feature map of the respective region from the contracting path. To ensure congruence, trimming is conducted before overlaying due to the slight variance in feature map sizes. The final stage involves performing two 3×3 and one l×l convolution operations on the overlaid feature map. However, the network faces two significant challenges. Firstly, the efficiency of the network is degraded due to computations being performed iteratively for each neighborhood, including repetitive calculations for overlapping neighborhoods. Additionally, the network encounters a trade-off between achieving accurate localization and gathering contextual information. Choosing a larger patch size requires the inclusion of extra maximum pooling layers, compromising the precision of object location. Conversely, opting for a smaller neighborhood results in a reduction of contextual information. Figure 1 illustrates the architectural representation of the U-Net network.

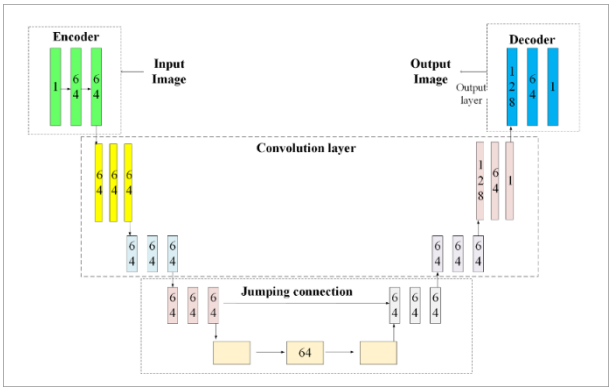

Figure 1: The network structure of U-Net

When employing the U-Net network structure for feature extraction and modeling design in architectural images, Figure 1 illustrates the architecture of this network. In this context, the input image represents architectural images or related data in the field, with the primary research objective being semantic segmentation—separating buildings from the background to explore the features, structures, and properties of the buildings. This study selects the U-Net network structure due to its exceptional performance in image segmentation tasks, simultaneously preserving detailed and semantic information. This provides a robust tool for achieving the research goals. Through this structure, this study aims to present a transparent and organized approach, elucidating how this algorithm extracts features from architectural images and its practical applications in architectural modeling and design.

Building upon the previously discussed content, this study aims to optimize the effectiveness of the U-Net network in capturing intricate texture details and global semantic structures efficiently. The objective is to achieve accurate and comprehensive image restoration by incorporating content loss functions and dual-transfer operations into the U-Net network. The dual-transfer operation is a mechanism introduced to enhance the restoration of significantly missing architectural images while preserving textures and global semantic structures. The core concept involves repairing missing regions by leveraging information from known regions to obtain updated estimations of image information. Unlike the original U-Net, which only performs inter-layer skip connections to transfer local features, the dual transfer mechanism performs feature transfer and re-encoding between two parallel networks to achieve cross-scale semantic and texture dual fusion. Within the U-Net network structure, the dual-transfer operation encompasses the establishment of transfer connection layers, capturing encoder and decoder features, identifying missing regions, and conducting nearest-neighbor searches. This operation facilitates the sharing of

feature representations between two parallel main structures, ensuring that estimated values for missing regions receive ample information while retaining crucial image details. Ultimately, this approach enhances the quality of restoration. The optimization process of the U-Net network using content loss functions and dual-transfer operations is delineated as follows: The U-Net framework incorporates two separate transfer connection layers.

The aforementioned layers have a parallel structure that mirrors the topology of the L layer in U-Net. The provided formulation denotes $\boldsymbol{\Phi_l(I)}$ and $\boldsymbol{\Phi_{L-l}(I)}$ as the encoder features that collect information from the $\boldsymbol{l}$-th and $(\boldsymbol{L-l})$-th layers, respectively. The objective is for $\boldsymbol{\Phi_l(I)}$ and $\boldsymbol{\Phi_{L-l}(I)}$ to encompass the majority of the relevant information contained in $\boldsymbol{\Phi_l(I^{gt})}$. For every arbitrary position $\boldsymbol{y \in \Omega}$, it follows that $\boldsymbol{(\Phi_l(I))_y \approx 0}$. Consequently, $\boldsymbol{(\Phi_{L-l}(I))_y \approx 0}$, indicating that it provides the same information as $\boldsymbol{\Phi_l(I^{gt})_y}$. The transfer connection layers $\boldsymbol{\Phi^{shift}_{L-l}(I)}$ and $\boldsymbol{\Phi^{shift}_{L-l+1}(I)}$ utilize $\boldsymbol{\Phi_l(I)}$ and $\boldsymbol{\Phi_{L-l}(I)}$, as well as $\boldsymbol{\Phi_{L-l}(I)}$ and $\boldsymbol{\Phi_{L-l+1}(I)}$, to derive an updated estimation of $\boldsymbol{\Phi_l(I^{gt})}$. The procedure involves the identification of the unknown region $\boldsymbol{\Omega}$ and the known region $\boldsymbol{\bar{\Omega}}$. Eq. (1) can be utilized to perform a nearest neighbor search (NNS) based on $\boldsymbol{\Phi_l(I)_x}$, where $\boldsymbol{x \in \bar{\Omega}}$, for each $\boldsymbol{(\Phi_{L-l}(I))_y}$, with $\boldsymbol{y \in \Omega}$.

$$\boldsymbol{X^*(y) = \arg\max_{x \in \bar{\Omega}} \frac{<(\Phi_{L-l}(I))_y, (\Phi_l(I))_x>}{\|(\Phi_{L-l}(I))_y\|_2 \|(\Phi_l(I))_x\|_2}} \quad (1)$$

For each $\boldsymbol{(\Phi_{L-l+1}(I))}$, with $\boldsymbol{y \in \Omega}$, an NNS based on $\boldsymbol{\Phi_{l-1}(I)_x}$ is conducted, where $\boldsymbol{x \in \bar{\Omega}}$, as delineated by Eq. (2).

$$\boldsymbol{X^*(y) = \arg\max_{x \in \bar{\Omega}} \frac{\langle(\Phi_{L-l+1}(I))_y, (\Phi_{l-1}(I))_x\rangle}{\|(\Phi_{L-l+1}(I))_y\|_2 \|(\Phi_{l-1}(I))_x\|_2}} \quad (2)$$

The estimations of $\boldsymbol{\Phi_l(I^{gt})_y}$ and $\boldsymbol{\Phi_{l-1}(I^{gt})_y}$ are subsequently revised through spatial rearrangements concerning the encoder features $\boldsymbol{\Phi_l(I)_x}$ and $\boldsymbol{\Phi_{l-1}(I)_x}$ [20]. The mathematical formulation of this can be expressed as follows:

$$\boldsymbol{\left(\Phi^{\text{shift}}_{L-l}(I)\right)_y = (\Phi_l(I))_{y+u_y}} \quad (3)$$

$$\boldsymbol{\left(\Phi^{\text{shift}}_{L-l+1}(I)\right)_y = (\Phi_{l-1}(I))_{y+u_y}} \quad (4)$$

Figure 2 portrays the U-Net structure with two special transfer connection layers.

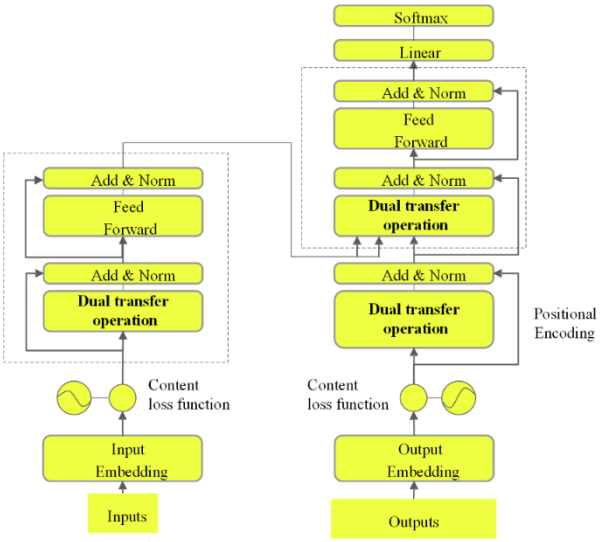

Figure 2: U-Net with two special transfer connection layers

A content loss function based on advanced image features is introduced to enhance the network's capability to capture intricate texture details. This approach involves extracting the high-level feature representations of both the decoder and encoder features corresponding to the original image's missing region. Subsequently, the mean squared error (MSE) is computed. The encoder examines the feature information of the image and extracts local features from it, while the decoder utilizes these local features to produce complex spatial and detailed structural information for the fragmented areas. The integration of encoders and decoders is facilitated through a hopping connection, which combines predictions from various feature layers. This mechanism allows for concurrently predicting local and global information, thereby enhancing the decoder's ability to effectively restore missing regions.

This study proposes the content loss function to depict the association between $\boldsymbol{\Phi_{L-l}(I)_y}$ and $\boldsymbol{\Phi_l(I^{gt})_y}$. The mathematical expression for this relationship is presented in Eq. (5).

$$\boldsymbol{L_{content} = \frac{1}{2}\sum_{y \in \Omega}\left((\Phi_{L-l}(I))_y - \left(\Phi_l(I^{gt})\right)_y\right)^2} \quad (5)$$

Eq. (6) describes the relationship between $\boldsymbol{(\Phi_{L-l+1}(I))_y}$ and $\boldsymbol{\Phi_{l-1}(I^{gt})_y}$.

$$\boldsymbol{L_{content} = \frac{1}{2}\sum_{y \in \Omega}\left((\Phi_{L-l+1}(I))_y - \left(\Phi_{l-1}(I^{gt})\right)_y\right)^2} \quad (6)$$

Given that $\boldsymbol{\Phi_l(I)_x \approx \Phi_l(I^{gt})_x}$ for every $\boldsymbol{x \in \bar{\Omega}}$, and $\boldsymbol{\Phi_{l-1}(I)_x \approx \left(\Phi_{l-1}(I^{gt})\right)_x}$, the content loss is confined to $\boldsymbol{y \in \Omega}$ to ensure $\boldsymbol{(\Phi_{L-l}(I))_y \approx \left(\Phi_l(I^{gt})\right)_y}$, and $\boldsymbol{\Phi_{L-l+1}(I)_y \approx \left(\Phi_{l-1}(I^{gt})\right)_y}$. The fusion of $\boldsymbol{\Phi_l(I)}$ and $\boldsymbol{\Phi_{L-l}(I)}$ captures nearly all the information in $\boldsymbol{\Phi_l(I^{gt})}$,

while the combination of $\boldsymbol{\Phi_{l-1}(I)}$ and $\boldsymbol{\Phi_{L-l+1}(I)}$ approximates all the information in $\boldsymbol{\Phi_{l-1}(I^{gt})}$ [21].

Furthermore, this study employs the foundational U-Net network model. Subsequently, an enhancement is introduced wherein conventional convolutional layers are replaced with partial ones. Specifically, the sliding window of these partial convolutional layers exclusively executes convolution operations within the pertinent image area. This innovation empowers the prediction of architectural constructions that incorporate asymmetrical gaps and simplifies the creation of renovation results featuring meaningful semantic characteristics.

3 Design of digital building file data manager system(blockchain-based cloud storage system)

The preceding section introduces the U-Net network and its enhancements. U-Net, a well-established convolutional neural network employed for image segmentation, incorporates compression and expansion paths. However, challenges related to efficiency and the balance between localization and contextual information are encountered. To address these challenges, an enhanced U-Net structure featuring specialized transfer connection layers is introduced in this study to elevate the precision and quality of image restoration. The subsequent section provides an in-depth exploration of the detailed design of the digital architectural document data management system, which adopts a blockchain-based cloud storage system. A comprehensive overview of the blockchain's structure and principles is provided, elucidating how it ensures data security and immutability. Simultaneously, the structure and operational principles of the blockchain-based cloud storage system are introduced.

The blockchain serves as a distributed transaction data structure [22, 23], facilitating the documentation of transaction details among nodes and ensuring data integrity through algorithms. It establishes a decentralized shared ledger, facilitating the verification and traceability of ledger information. The blockchain validates and stores data within a chain structure by employing cryptographic algorithms. Consensus mechanisms are employed to generate and update data across a distributed network, frequently utilizing smart contracts for data manipulation and coding. Consequently, blockchain technology achieves decentralized management and ensures equal rights across all blockchain nodes, mitigating delays and storage risks inherent in centralized systems [24-27]. The fundamental data unit in the blockchain is referred to as a block, forming a unidirectional chain structure by linking parent block hashes sequentially. Each block comprises a header and a body. The header contains metadata, and data block authenticity is ensured through hash verification. The interconnection between blocks is established by the parent block's hash, with the block's hash generated through the SHA-256 function. Notably, modifications in one block impact subsequent blocks, including the header and Merkle root hashes, rendering any attempt to introduce false data into the blockchain by maliciously altering node information unfeasible [28, 29]. The feasibility of achieving such an accomplishment is hindered by the substantial size of network manipulation necessary, which necessitates the utilization of around 50% of the network's processing power. The block's structural composition within the blockchain framework is illustrated in Figure 3.

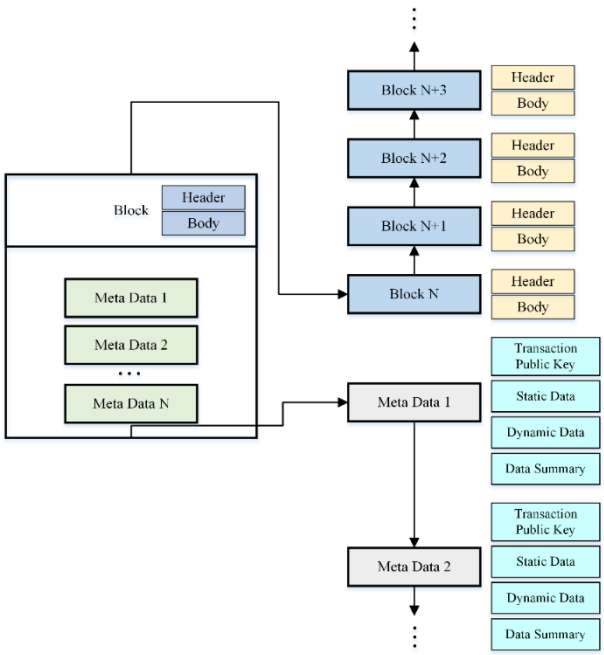

Figure 3: Block structure of the blockchain

Figure 3 illustrates that the block structure within the blockchain comprises two primary components: the header and the body. The header encompasses metadata elements, including timestamps and the hash value of the preceding block, establishing crucial links between consecutive blocks. The block's integrity is upheld through hash verification, wherein any tampering with block data alters its hash value, compromising the blockchain's overall coherence. Meanwhile, the body section accommodates actual transaction data or other relevant information, with the specific content contingent upon the blockchain's intended application. The blocks within the blockchain are systematically interconnected in chronological order, giving rise to a chain-like structure. This interconnection ensures both the immutability and sequential arrangement of data, endowing the blockchain with elevated security and traceability.

Based on blockchain technology, the envisaged cloud storage system encompasses four distinct roles: museums, governments, ordinary users, and professional restorers. Furthermore, this ecosystem involves the participation of blockchain nodes, as depicted in Figure 4.

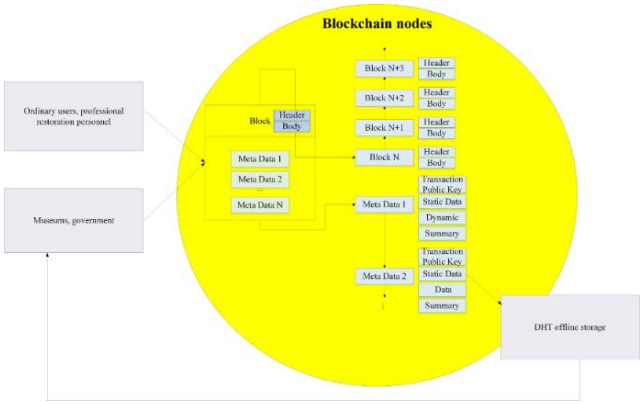

Figure 4: The cloud storage system based on blockchain

4 Enhancing texture and contextual feature restoration

This section discusses the implementation of the approach to enhance the restoration of texture and contextual features in cultural heritage images.Data Preprocessing: Before initiation, essential preprocessing steps are performed on the input data. These include image resizing, color space conversion, and noise removal, ensuring that the input data is optimized for network processing.Neural Network Architecture: The chosen neural network model is the optimized U-Net architecture, featuring an encoder for extracting image features and a decoder for generating the restored image.Loss Function: The Content Loss function is selected, employing mean squared error loss to gauge the dissimilarity between the generated and original images. The objective is to minimize the Content Loss, compelling the network to learn the feature representation of the original image, encompassing texture, and contextual features.Dual-Transfer Operation: This entails sharing feature representations within the backbone structure through parallel connections and nearest neighbor search. Nearest neighbor search aligns features from known regions with features from missing regions, enhancing the accuracy of estimates.Image Generation and Output: Following the completion of network training, the image to be restored is input into the network to generate the restored image.Drawing upon the content discussed in the preceding sections, this study integrates the improved U-Net neural network with a blockchain-based data storage and sharing system to realize the comprehensive algorithmic flow for image restoration, as depicted in Figure 5.

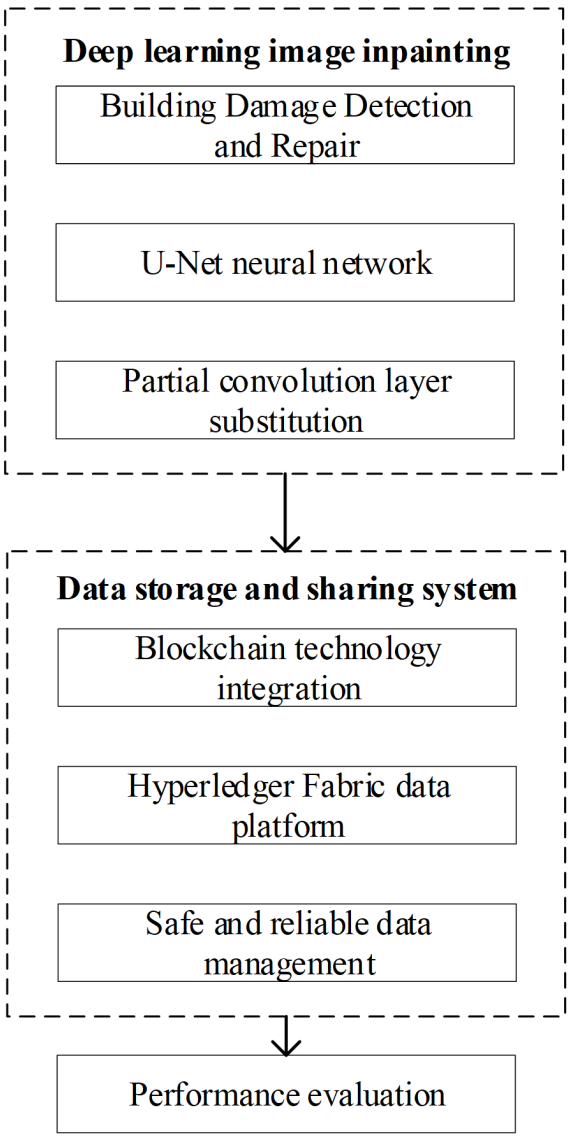

Figure 5: Algorithmic flow

5 Experimental data and evaluation index

This section outlines the experimental configuration aimed at assessing the performance of the previously proposed model. The experimental design encompasses the data source, data preprocessing, experimental environment, and the establishment of performance evaluation metrics.

The experimental data employed in this study originates from the WHU building dataset created by the Ji Shunping Team at Wuhan University. This dataset constitutes a collection of internationally standardized datasets designed for building extraction (available at http://study.rsgis.whu.edu.cn/pages/download/). The

building dataset consists of aerial images with a spatial resolution of 0.3 meters. These photos include three visible bands—Red, Green, and Blue (RGB). The dataset covers an expansive area of 400 square kilometers and includes a diverse array of 180,000 buildings, exhibiting variations in size, color, and function. Figure 6 depicts sample images extracted from the dataset employed in these experiments.

Figure 6: Pictures of dataset samples

The utilization of these metrics aids in evaluating the model's robustness to noise, ensuring accuracy and reliability in the extraction and modeling of building features. The specific details of the evaluation metrics are outlined below:

The Structural Similarity Index Measure (SSIM) is employed to quantify the similarity between the actual and generated images in deep learning-based image restoration. This approach aligns with human perceptual evaluation standards for assessing image quality by evaluating brightness, contrast, and structural information. The technique of contrast estimation involves the use of the standard deviation (SD), while brightness estimation relies on the mean value. SSIM is quantified using covariance. To compute the similarity between two input images, denoted as x and y, the SSIM is formulated as shown in Eq. (7).

$$SSIM(x,y) = l(x,y) \cdot c(x,y) \cdot s(x,y) \tag{7}$$

In Eq. (7), l(x, y) represents the luminance similarity factor, assessing the likeness of image luminance to ensure the robustness of the results against luminance variations. Similarly, c(x, y) denotes the contrast similarity factor employed to gauge the similarity of image contrast, ensuring resilience to contrast variations. Finally, s(x, y) signifies the structural similarity factor utilized to measure the similarity of image structure, ensuring the robustness of the results to structural variations. The methodologies for these three factors are elucidated as follows:

$$l(x,y) = \frac{2u_x u_y + c_1}{u_x^2 + u_y^2 + c_1} \tag{8}$$

$$c(x,y) = \frac{2\sigma_x \sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \tag{9}$$

$$s(x,y) = \frac{\sigma_{xy} + c_3}{\sigma_x \sigma_y + c_3} \tag{10}$$

where $\boldsymbol{u_x}$ and $\boldsymbol{u_y}$ represent the mean of images x and y, and $\boldsymbol{\sigma_x}$ and $\boldsymbol{\sigma_y}$ represent their SDs; $\boldsymbol{\sigma_x^2}$, $\boldsymbol{\sigma_y^2}$, and $\boldsymbol{\sigma_{xy}}$ stand for the variance and covariance of images x and y, respectively; Additionally, the constants $\boldsymbol{c_1}$, $\boldsymbol{c_2}$, and $\boldsymbol{c_3}$ are included to prevent division by zero. Usually, $\boldsymbol{c_1}$, $\boldsymbol{c_2}$, and $\boldsymbol{c_3}$ are defined as $\boldsymbol{(k_1 l)^2}$, $\boldsymbol{(k_2 l)^2}$, and $\boldsymbol{c_2/2}$, respectively. The interrelation between these quantities is illustrated in Eq. (11).

$$\mathrm{SSIM}(x,y) = \frac{(2u_x u_y + c_1)(2\sigma_{xy} + c_2)}{(u_x^2 + u_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{11}$$

The process involves extracting N×N windows from the image and calculating their respective averages. The global SSIM value is determined by utilizing the resulting average [30].

The PSNR is utilized as a quantitative measure for evaluating photographs objectively. It calculates the disparity at the pixel level between the generated images and the ground truth images [31]. The PSNR is determined by calculating the MSE between the current image x and the reference image y.

$$\boldsymbol{MSE = \frac{1}{h \times w} \sum_{i=1}^{h} \sum_{j=1}^{w} [x(i,j) - y(i,j)]^2} \tag{12}$$

In Eq. (12), *h* and w stand for the image's height and width, respectively; the PSNR is defined in Eq. (13) [32].

$$PSNR = 10 \log_{10} \left(\frac{(2^n - 1)^2}{MSE} \right) \tag{13}$$

Additionally, this study employs the Learned Perceptual Image Patch Similarity (LPIPS) metric to quantify image similarity. LPIPS is a perceptual image patch similarity metric designed to evaluate perceptual differences between images. Specifically, LPIPS utilizes a neural network to learn the perceptual features of image patches, calculating the distance between them to quantify the perceptual similarity of images, expressed as follows:

$$LPIPS(x,y) = \sum_{i=1}^{n} \omega_i \cdot \varphi_i(x) \cdot d_i\big(\varphi_i(x), \varphi_i(y)\big) \tag{14}$$

In Eq. (14), x and y represent two images, $\boldsymbol{\varphi_i(x)}$ denotes the representation of the i-th feature layer, $\boldsymbol{d_i}$ signifies the distance measurement function on that feature layer, and $\boldsymbol{\omega_i}$ denotes the weight for the corresponding feature layer.

The suggested prediction model is validated through simulation tests on a specialized platform. After gathering, preparing historical data, and creating a validation set, the proposed model and the training models are applied to both the training and validation sets to calculate losses. The training process concludes when the model's loss on

the validation set no longer shows a decline. The subsequent simulations are conducted using a Windows 10 operating system, featuring a 3.0GHz CPU, 4GB of RAM, and a central processing unit core-i7-7700HQ.

6 Experimental results and discussion

This chapter offers a comprehensive presentation and analysis of the performance results obtained from the enhanced algorithmic model. The primary objective is to validate the practicality and reliability of the model through a meticulous examination of its outcomes.

6.1 Test and analysis of the proposed improved algorithm

The primary objective of the developed algorithm is to restore building images. Figure 7 depicts the performance of the algorithm in restoring building pictures within the dataset of Wuhan University buildings.

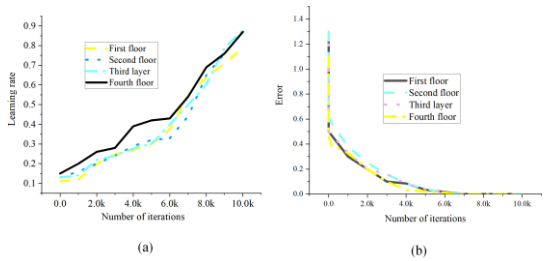

Figure 7: Verification results of the improved model ((a) depicts the verification results of the model improvement layer's learning rate, and (b) showcases the error analysis verification of the same layer.)

The observations from Figure 7 indicate notable advantages of the model. Firstly, the learning rate of the model shows a consistent increase throughout the iterations. Notably, after around 10,000 iterations, the learning rate settles at approximately 0.9, highlighting the model's robust learning capacity. Moreover, in the context of error verification, the model's error progressively decreases as the number of iterations increases. When the number of iterations reaches 10,000, the model's error exhibits significant convergence towards zero.

Figure 8 illustrates the correlation between the iteration count of the enhanced model and the PSNR value.

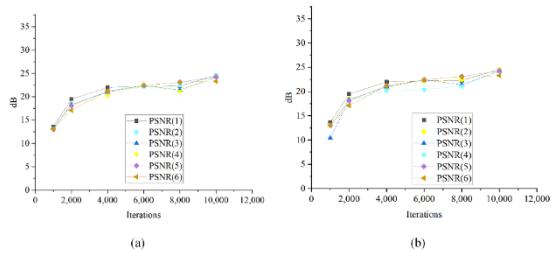

Figure 8: Iteration count vs. PSNR value (a. First Test; b. Second Test)

In Figure 8, the PSNR values corresponding to algorithm iterations of 1,000 and 10,000 are 24.21 and 26.16, respectively. It is observed that the quality of image generation improves with increased iterations. Moreover, beyond 10,000 iterations, the generated images approach benchmark quality.

6.2 Performance validation of the model

(1) Evaluation of PSNR, SSIM, and LPIPS values of the model

The quantitative evaluation involves assessing and comparing various image restoration algorithms by quantifying PSNR, SSIM, and Learned Perceptual Image Patch Similarity (LPIPS) metrics. Fifty validation images are randomly selected for this purpose, and the average values of SSIM, LPIPS, and PSNR are computed. The PSNR, SSIM, and LPIPS values for different methods are presented in Table 1. In this context, LPIPS distinguishes itself from conventional image quality assessment metrics like PSNR and SSIM. LPIPS places heightened importance on scrutinizing perceptual details within images, encompassing considerations such as structure, color distribution, and texture. In the realm of image restoration, LPIPS proves invaluable for appraising the perceptual similarity between generated or restored images and their original counterparts, delivering a quality assessment more attuned to the intricacies of the human visual system. Consequently, LPIPS enjoys broad applicability in the domains of deep learning and computer vision, particularly in tasks where emphasis is placed on perceptual quality, allowing for a more precise evaluation of the efficacy of image generation algorithms.

Table 1: Quantitative evaluation

Method (Model iteration)	PSNR	SSIM	LPIPS	Total Variation
Patch Match [33]	20.57	0.31	0.891	0.125
Context Encoder [34]	22.71	0.41	0.861	0.114
Globally and Locally [35]	21.21	0.35	0.851	0.121
Shift Net [36]	21.78	0.28	0.794	0.135
U-net [37]	21.32	0.34	0.723	0.132
Res Net [38]	24.82	0.52	0.798	0.112
Generative Adversarial Network [39]	25.94	0.55	0.783	0.109
The proposed algorithm	26.16	0.57	0.825	0.102

Table 1 illustrates that the proposed algorithm exhibits the highest PSNR value compared to the other comparative algorithms. This observation implies that the proposed algorithm generates the least error between corresponding pixels within the restored image compared to the original image. Moreover, the proposed algorithm minimizes texture distortion in the missing region, resulting in an image that closely resembles the original. Notably, the SSIM value for the proposed algorithm also outperforms other algorithms, indicating superior

restoration of brightness, contrast, and semantic structure in the image.

Moreover, as illustrated in Table 1, the algorithm presented here demonstrates comparatively diminished performance on the LPIPS evaluation metric in comparison to Patch Match, Context Encoder, Globally and Locally, and Shift Net. This discrepancy can be attributed to LPIPS functioning as a perceptual similarity measure, mirroring the subjective way in which humans perceive image similarity. Its scores are influenced by factors such as image structure, color distribution, and texture. Notwithstanding the lower scores on LPIPS in this study, the algorithm exhibits commendable performance on traditional evaluation metrics like PSNR and SSIM, indicating an overall satisfactory outcome.

(2) Feature extraction performance of the model

The algorithm proposed here demonstrates its proficiency in feature extraction when applied to the two target images as illustrated in Figure 6. The resulting output is presented in Figure 9.

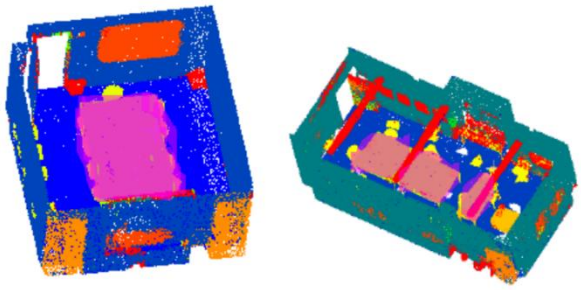

Figure 9: Output results of the model

Figure 9 illustrates the exceptional performance of the proposed algorithm in indoor scene recognition, with a specific focus on detailing the model's outputs in images containing furniture. Firstly, the model exhibits a high degree of pixel-level accuracy in recognizing subtle differences in chair designs. Secondly, the model excels in precisely identifying and differentiating images on walls, even in scenarios with numerous visual elements. This capability is pivotal for effectively handling the diverse range of visual elements present in indoor scenes. Furthermore, the model performs remarkably well in the broader context of semantic segmentation and excels in the precise instance segmentation of complex sofa point clouds. The ability to intricately understand spatial relationships enables the model to accurately delineate various instances of sofas within semantic scenes. These detailed and nuanced visual results underscore the model's exceptional performance and enhance the understanding of its capabilities in addressing diverse indoor scenes, offering a more comprehensive perspective on its overall efficacy in indoor scene recognition tasks.

6.3 Comparison of storage system performance

The performance of the system proposed here is compared to that of an existing cloud storage system. Two systems are considered in this analysis. The system outlined in Reference [40] entails a full-text retrieval mechanism for safeguarding the privacy of encrypted data within cloud storage. Meanwhile, the approach presented in Reference [41] outlines a cost-effective cloud storage scheme involving mixed strategies. The comparative performance analysis between the proposed system and the existing counterparts is depicted in Figure 10.

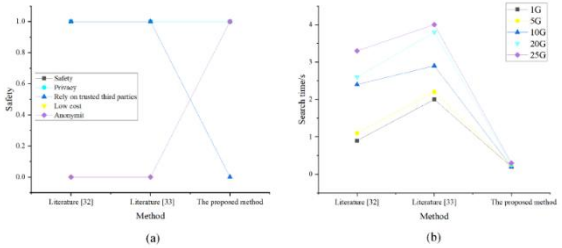

Figure 10: Performance comparison results between the proposed system and the existing cloud storage system (a: Basic performance; b: Data storage performance)

Figure 10(a) depicts the proposed blockchain-based data storage system designed to preserve historical structures. This system provides secure, private, cost-efficient, and anonymous storage and retrieval services, eliminating the necessity for a trusted middleman. Notably, its performance outpaces that of the other two cloud storage systems. Moving to Figure 10(b), it becomes apparent that the search time for data across the three storage systems increases as the data storage capacity increases. Within varying levels of stored data, the proposed data storage system exhibits shorter search times compared to the other two systems. This advantageous outcome is attributed to the system's utilization of blockchain as the underlying framework for offline data storage, authorization, access, and search token generation. This strategic employment ensures data security while concurrently curtailing search times, thereby underscoring the effectiveness of the proposed system.

6.4 Data storage cost and efficiency analysis

Figures 11(a) and 11(b) effectively depict the upward trajectory of both observed and projected expenditure values during the conservation process of historical building restoration data in the XX province. The provided figures accurately depict the changes observed before and after the introduction of the proposed system. Figure 11(a) demonstrates a noticeable increase in expenditure for the preservation project of historic building repair data in the XX province over the years 2016, 2017, 2018, 2019, and 2020. The recorded values for the years 2015, 2016, 2017,

2018, and 2019 were 549,400, 647,400, 781,100, 1,007,800, and 1,124,800 CNY, respectively. Figure 11(b) presents a predictive study that anticipates the incremental spending values for linked projects in the XX province from 2016 to 2020. The projected values for each year are as follows: 249,400 CNY for 2016, 347,400 CNY for 2017, 481,100 CNY for 2018, 607,800 CNY for 2019, and 724,800 CNY for 2020. These values represent the increase in expenditure compared to the preceding year. This data illustrates a notable improvement of 25%, 24%, 26%, 25%, and 25% in efficiency compared to the original approach. The methods for building restoration presented in this study are expected to result in an annual cost reduction of 1 million CNY.

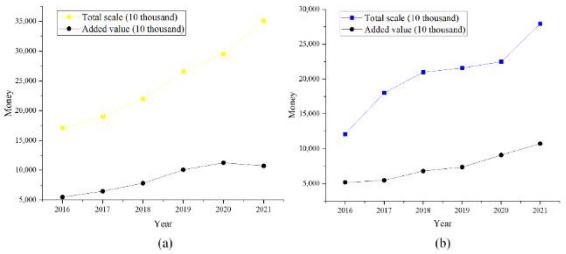

Figure 11: Statistics of restoration costs of historic buildings in the xx province (a. actual value; b. predicted value.

7 Conclusion

The preservation of ancient architectural designs holds considerable national significance, leading to the adoption of contemporary computer technologies for digitization and restoration. This study presents a novel picture restoration model for ancient buildings utilizing the U-Net architecture. The methodology employs the U-Net architecture as the fundamental network model, later enhancing it by substituting all convolutional layers with partial equivalents. Moreover, the partial convolutional layer employs a sliding window mechanism to perform convolutions only inside relevant portions of the picture. This allows for the accurate prediction of building structures containing irregular voids and the development of restoration results with semantic significance. The present study proposes the development of a platform utilizing blockchain technology to effectively store and manage historical building maintenance data. This platform aims to fulfill the specific requirements of a data storage and sharing system for the aforementioned purpose. The experimental results illustrate the effectiveness of the method in successfully reconstructing photographs of historical structures, minimizing MSE, and exhibiting robust practicality and possible use in real-world situations. The neural network evaluations demonstrate that the algorithm under consideration achieves SSIM, LPIPS, and PSNR scores of 0.57, 0.725, and 26.16, respectively. Future investigations aim to replace the existing backbone network with a residual network and enhance the model's up-sampling process to reduce the impact of injected noise. These endeavors are expected to improve the model's overall efficacy and performance.

Future research will further introduce Transformer backbone structures (such as Swin-UNet and ConvNeXt-UNet) to enhance the global modeling capabilities of feature expression. Simultaneously, we will explore diffusion-based image restoration methods to improve complex textures and semantic consistency. Furthermore, we will study blockchain-based model provenance and tracking mechanisms to ensure the verifiability and credibility of the restoration process and data management.

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Research on the Integration and Creation of Intangible Cultural Heritage in the Inheritance of Qinling Culture.

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Federated Deep Learning-Based Collaborative Optimization and Privacy Preservation in Microgrid Clusters Using GRU Models

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To address the challenges faced in optimizing the operation of distributed power generation systems, this study proposes an innovative method. The method integrates GRU deep learning to model temporal operational patterns and federated learning to enable privacy-preserving collaborative optimal operation of microgrid clusters. This model employs data augmentation techniques to build local encapsulated models and leverages federated learning to achieve strategy evolution. Case analysis demonstrates that this approach excels in prediction accuracy (test RMSE of 12.5), operational cost control (reducing total cost by 15.1% compared to independent operation), and computational speed, while also offering significant advantages in privacy protection. It provides an effective solution for the optimal operation of microgrid clusters.

Povzetek: Študija predlaga inovativno metodo, ki z združitvijo globokega učenja GRU in federativnega učenja omogoča učinkovito, optimalno upravljanje gruč mikroomrežij.

1 Introduction

In the context of global energy transition and the rapid development of smart grids, the integration of distributed energy sources (such as wind and solar energy) with microgrid technologies has emerged as a pivotal approach to enhancing energy utilization efficiency and optimizing distribution systems [1]. With the continuous advancement and cost reduction of renewable energy technologies, the deployment scale of distributed energy is rapidly expanding [2], presenting new opportunities and challenges for the flexibility and sustainability of power systems. However, the coordinated optimal operation of microgrid clusters remains fraught with challenges [3], and how to achieve efficient, secure, and reliable operation has become a critical research topic in the field of intelligent distribution systems both domestically and internationally.

Although traditional centralized optimization methods can achieve global optimization, they are highly dependent on communication networks and pose risks of privacy leakage [4], making them unsuitable for distributed scenarios involving multiple microgrid clusters. Distributed optimization methods, utilizing consensus algorithms [5] or game theory [6], have enhanced both economic efficiency and reliability, but they face limitations in terms of profit allocation, privacy protection, and the effectiveness of global optimization [7]. With the continuous progress of artificial intelligence and big data technologies, data-driven optimization methods have offered new insights for the coordinated optimal operation of multi-microgrid clusters [8]. Optimization methods based on reinforcement learning [9] can achieve rapid solutions through real-time data-driven approaches, but their stochastic exploration process may lead to local optima or convergence issues. Moreover, centralized data-driven methods also face challenges related to data privacy and communication bottlenecks, while distributed methods still encounter technical limitations in power interaction patterns and profit allocation calculations [10]. Therefore, how to achieve efficient and coordinated optimization of multi-agent microgrid clusters while protecting privacy has become a critical issue that demands immediate resolution.

To address these issues, this paper proposes a federated learning-based collaborative optimization and strategy evolution method for multi-agent microgrid clusters. This method involves uploading encapsulated models of each microgrid to the cloud for global strategy search [11] and conducting distributed joint training of horizontal federated neural networks [12,13] to achieve dynamic strategy evolution. The proposed approach addresses key limitations of existing methods by enabling privacy-preserving collaborative learning without raw data sharing, thanks to model encapsulation and cryptographic techniques. This approach not only effectively protects the data privacy of each microgrid but also enhances the collaborative operation efficiency of microgrid clusters, providing new insights for realizing smarter and more efficient energy management systems.

2 Related work

Currently, research on the optimal operation of microgrid clusters primarily focuses on two categories of methods: model-driven and data-driven approaches [14]. Model-driven methods achieve optimization by constructing objective functions and constraints through mathematical modeling. For instance, centralized

optimization methods [15] employ a central controller to manage the entire microgrid cluster, enabling global optimization, but they are highly dependent on communication networks and pose risks of privacy leakage, making them unsuitable for multi-agent scenarios.

Distributed control methods enhance economic efficiency and reliability through consensus algorithms, but they fail to adequately address the issue of profit allocation among individual microgrids [16] and face challenges related to communication delays and consensus. Game theory methods [17] can optimize the system through interactions among multiple agents, eliminating the need for centralized control and enhancing system reliability and stability, but their solution process is complex and does not fully consider privacy protection. While classical control methods like adaptive fuzzy control [18] and backstepping control [19] excel in handling system nonlinearities and uncertainties for stabilization tasks in single systems (e.g., robotic manipulators [20] or compressors [21]), they are less suited for multi-agent, data-driven collaborative optimization where privacy and data decentralization are paramount. Table 1 summarizes the key characteristics of representative methods, highlighting limitations in privacy, global optimization capability, and scalability that this work aims to address.

Table 1: Comparison of microgrid cluster optimization methods

Method Category	Cost Performance	Privacy Preservation	Global Optimization
Centralized Optimization [15]	High	Very Low	Strong
Distributed Optimization[5], [16]	Medium	Low	Medium
Game Theory[6], [17]	Medium-High	Low	Weak
Deep Reinforcement Learning[9]	Medium-High	Low	Medium
Proposed (FL+GRU)	High	High	Strong

As an emerging paradigm for privacy-preserving collaborative learning, Federated Learning (FL) has seen recent research efforts explore its integration with domain-specific physical models or spatiotemporal structures to enhance model practicality and reliability. Our method aim to address a different facet of system control: enabling secure, collaborative strategy learning among multiple self-interested agents (microgrids) without raw data sharing. The proposed FL framework prioritizes privacy-preserving cooperation over direct system stabilization, making it complementary to, rather than a replacement for, classical robust control in complex systems.

3 Method introduction

3.1 Cloud-edge collaborative optimization strategy

This paper proposes a cloud-edge collaborative optimization strategy based on federated neural network learning [22], tailored for distributed power generation systems. Strategy Evolution is applied to describe the iterative process where the global operational strategy, encoded in the federated model parameters, is progressively refined through cycles of local execution, encrypted model update uploads, secure aggregation on the cloud, and subsequent distribution of the improved global model back to the microgrids. The fundamental framework of the microgrid cloud-edge collaborative optimization strategy is structured into three layers, as depicted in Figure 1. The bottom layer constitutes the physical layer of microgrid clusters, encompassing multiple microgrids, each equipped with power devices and control systems. The intermediate layer serves as the global strategy search layer, comprising numerous encapsulated models, each corresponding to a microgrid. These encapsulated models are interconnected via an interaction network and a learning network, primarily responsible for searching and optimizing global strategies, thereby providing optimized strategies for the microgrid cluster. The topmost layer is the FL evolution layer, primarily composed of a learning network. By communicating with the interaction network and encapsulated models in the lower layers, this layer employs federated learning algorithms to evolve and optimize strategies to accommodate the operational requirements of the microgrid cluster, consequently enhancing the operational efficiency and reliability of the microgrid cluster.

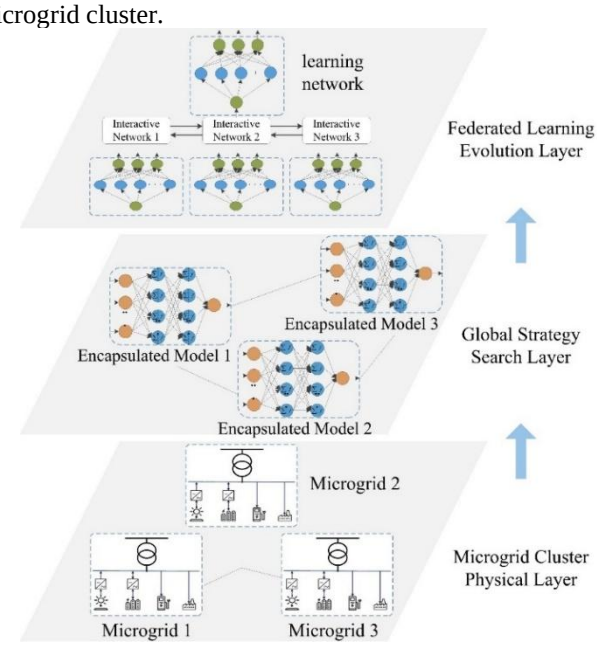

Figure 1: Basic framework of cloud-edge collaborative optimization strategy for microgrids

3.2 Collaborative optimization model for microgrid clusters

3.2.1 Objective function

In the optimization model of a microgrid, the objective is to minimize the daily operational cost of the microgrid. The objective function is expressed as follows:

$$\min C_{\mathrm{MG},i} = \sum_{t=1}^{T}(C_{\mathrm{self},i,t} + C_{\mathrm{market},i,t}) \tag{1}$$

Herein, $C_{\mathrm{self},i,t}$ denotes the operational cost of all units within microgrid i at time t; $C_{\mathrm{market},i,t}$ represents the trading cost between microgrid i and the external market at time t, encompassing both electricity purchase expenses and sales revenue.

The computation of operational and maintenance expenditures $C_{\mathrm{OM},i,t}$ is delineated as follows:

$$C_{\mathrm{OM},i,t} = k_{\mathrm{PV}}P_{\mathrm{PV},i,t} + k_{\mathrm{WT}}P_{\mathrm{WT},i,t} + k_{\mathrm{GT}}P_{\mathrm{GT},i,t} + k_{\mathrm{ES}}\left|P_{\mathrm{ES},i,t}\right| \tag{2}$$

where, the subscripts $[\mathrm{PV},\mathrm{WT},\mathrm{GT},\mathrm{ES}]$ represent photovoltaic, wind turbine, gas turbine, and energy storage system, respectively; P and k denote the corresponding unit's power output and unit operating cost.

The fuel cost for the gas turbine, denoted as $C_{\mathrm{f},i,t}$, is calculated as follows:

$$C_{\mathrm{f},i,t} = c_{\mathrm{NG}}\frac{P_{\mathrm{GT},i,t}}{\eta_{\mathrm{GT}}L_{\mathrm{NG}}} \tag{3}$$

where, C_{NG} and L_{NG} represent the price of natural gas and its calorific value, respectively; while η_{GT} signifies the efficiency index of the gas turbine. The cost of life degradation for the energy storage device, denoted as $C_{\mathrm{NS},i,t}$, is calculated as follows.

$$C_{\mathrm{NS},i,t} = c_{\mathrm{NS}}\frac{P_{\mathrm{NS},i,t}}{L_{\mathrm{R}}D_{\mathrm{R}}E_{\mathrm{R}}} \tag{4}$$

where, c_{NS} signifies the unit power cost coefficient of the energy storage device; $P_{NS,i,t}$ represents the charge/discharge power of the energy storage device in microgrid i at time t; L_{R} denotes the cyclic life degradation coefficient; D_{R} indicates the depth of charge/discharge coefficient; and E_{R} stands for the energy efficiency coefficient.

The cost of electricity purchase and sale under the centralized transaction model, $C_{\mathrm{market},i,t}$, is calculated as follows.

$$C_{\mathrm{market},i,t} = e_{\mathrm{mg},i,t}(P_{\mathrm{grid},i,t} + \sum_{j\neq i}P_{\mathrm{mg},i,j,t}) \tag{5}$$

Herein, $e_{\mathrm{mg},i,t}$ denotes the net energy exchange of microgrid i at time t; $P_{\mathrm{grid},i,t}$ represents the transaction price between microgrid i and the main grid; $P_{\mathrm{mg},i,j,t}$ signifies the aggregate transaction price between microgrid i and other microgrids j.

In the operation of microgrid clusters, the trading mechanism f_{trade} serves as the linchpin for facilitating energy transactions and economic settlements among microgrids. This mechanism, predicated on the predetermined target trading power $P_{\mathrm{trade},t}$ and target trading price $e_{\mathrm{trade},t}$, derives the actual trading power $P_{\mathrm{mg},t}$ and trading price $e_{\mathrm{mg},t}$ through the settlement process.

$$(e_{\mathrm{mg},t}, P_{\mathrm{mg},t}) = f_{\mathrm{trade}}(P_{\mathrm{trade},t}, e_{\mathrm{trade},t}) \tag{6}$$

In the operation of microgrid cluster, the formulas for power balance and cost equilibrium are delineated as follows:

$$\sum_i P_{\mathrm{mg},i,t} = P_{\mathrm{grid,MGs},t} \tag{7}$$

$$\sum_i e_{\mathrm{mg},i,t}P_{\mathrm{mg},i,t} = e_{\mathrm{g},t}P_{\mathrm{grid,MGs},t} \tag{8}$$

where, $P_{\mathrm{grid,MGs},t}$ signifies the actual transactional power between the microgrid cluster and the main grid at time t; whereas $e_{\mathrm{g},t}$ represents the electricity tariff of the primary grid.

3.2.2 Constraints

When optimizing the operation of microgrid cluster, various constraints must be considered to ensure that the system meets both physical and economic requirements while remaining operationally viable.

1) Controllable power source power constraints:

The actual power output $P_{\mathrm{GT},i,t}$ of controllable power sources within microgrid i at time t is bounded by $P_{\mathrm{GT},i}^{\min}, P_{\mathrm{GT},i}^{\max}$.

$$P_{\mathrm{GT},i}^{\min},\ P_{\mathrm{GT},i,t},\ P_{\mathrm{GT},i}^{\max} \tag{9}$$

2) Power constraints for charging and discharging:

The state of the energy storage system at any given time, quantified by its State of Charge (SOC), along with the formulation for calculating its charging and discharging efficiencies, is delineated as follows [23].

$$S_{\mathrm{OC},t} = S_{\mathrm{OC},t-1} - \frac{P_{\mathrm{ES},i,t}\Delta t}{E_{\mathrm{R}}}\eta_{\mathrm{B}} \tag{10}$$

$$\eta_{\mathrm{B}} = \begin{cases} \eta_{\mathrm{BC}}, P_{\mathrm{ES},i,t} < 0 \\ \dfrac{1}{\eta_{\mathrm{BD}}}, P_{\mathrm{ES},i,t}..0 \end{cases} \tag{11}$$

$$S_{\mathrm{OC}}^{\min},\ S_{\mathrm{OC},t},\ S_{\mathrm{OC}}^{\max} \tag{12}$$

Herein, $P_{\mathrm{ES},i,t}$ signifies the power output of the energy storage system within microgrid i at time t, where BD denotes discharging and BC represents charging. The term Δt denotes the time step, while E_{R} represents the rated capacity of the energy storage system. Additionally, η_{B} denotes the efficiency of both charging and discharging processes, and the bounds of $S_{\mathrm{OC},t}$ are defined by $S_{\mathrm{OC}}^{\max}$ and $S_{\mathrm{OC}}^{\min}$.

Furthermore, it is stipulated that the energy storage system should maintain the same state of charge (SOC) at the commencement and conclusion of the optimization period, denoted respectively as $S_{\mathrm{OC},0}$ and $S_{\mathrm{OC},T}$.

$$S_{\mathrm{OC},0} = S_{\mathrm{OC},T} \tag{13}$$

The charge-discharge power constraint is expressed as follows.

$$\begin{cases} 0,\ P_{\mathrm{ES},i,t},\ P_{\mathrm{ES},i}^{\mathrm{BD}}, & P_{\mathrm{ES},i,t}..0 \\ -P_{\mathrm{ES},i}^{\mathrm{BC}},\ P_{\mathrm{ES},i,t} < 0, & P_{\mathrm{ES},i,t} < 0 \end{cases} \tag{14}$$

3) Transaction transmission power constraints:

In participating in market transactions, the microgrid's power output should stay within allowable limits to comply with market regulations and physical constraints. The minimum and maximum permitted power outputs of the microgrid in market transactions are denoted as $P_{\mathrm{market}}^{\min}$ and $P_{\mathrm{market}}^{\max}$, respectively.

$$P_{\mathrm{market}}^{\min},\ P_{\mathrm{market},i,t},\ P_{\mathrm{market}}^{\max} \tag{15}$$

4) Power balance constraint:

$$P_{\mathrm{PV},i,t} + P_{\mathrm{WT},i,t} + P_{\mathrm{GT},i,t} + P_{\mathrm{ES},i,t} + P_{\mathrm{mg},i,t} = P_{\mathrm{load},i,t} \tag{16}$$

where, P represents the power output of the corresponding units.

5) Transaction price constraint:

In the electricity transactions between microgrids, the transaction price $e_{\mathrm{mg},i,t}$ must satisfy the condition of being greater than the selling price $e_{s,t}$ and less than the purchasing price $e_{\mathrm{b},t}$.

$$e_{s,t},\ e_{\mathrm{mg},i,t},\ e_{\mathrm{b},t} \tag{17}$$

3.3 Global strategy search

3.3.1 Deep Learning-based local encapsulation model

Addressing the limitations of local encapsulation models in microgrids when dealing with various operating scenarios, due to historical data's inability to comprehensively cover all possible contexts, we propose a data augmentation method combining nonparametric kernel density estimation with Latin hypercube sampling [24]. The encapsulated model is a local surrogate model that abstracts the microgrid's operational cost function using a GRU network. This encapsulation allows the model to be shared in FL while preserving data privacy. Firstly, nonparametric kernel density estimation is employed to uncover the intrinsic characteristics of operational data, allowing for a more accurate reflection of the data distribution without relying on specific prior distribution assumptions. Subsequently, by integrating the estimated probability density function to obtain the cumulative distribution function, and applying Latin hypercube sampling techniques, a large number of simulated scenario data are generated.

$$(P_m, C_m) = f_{\mathrm{MG}}(S_m) \tag{18}$$

Herein, P_m denotes the power of each unit in the microgrid; f_{MG} represents the optimization model; C_m signifies the operational cost of the microgrid; S_m stands for the scenario data generated by sampling.

The article employs a deep learning network based on gated recurrent units (GRUs) for feature encapsulation [25]. GRU is chosen for its simpler structure compared to LSTM, reducing computational cost while maintaining strong performance in capturing short-term temporal dependencies. The encapsulation process involves initially training the GRU model using historical operational data to accurately forecast the operational costs of a microgrid. Subsequently, the trained model is encapsulated and uploaded to the cloud, where it is utilized for global policy search and optimization.

To enhance the robustness of the local encapsulated models against diverse and unseen operating conditions, we employ a data augmentation technique combining Nonparametric Kernel Density Estimation (KDE) and Latin Hypercube Sampling (LHS). The procedure is as follows:

1) Probability Density Estimation (KDE): For each uncertain variable v in a microgrid's historical dataset, we estimate its probability density function (PDF) using KDE:

$$\hat{f}_v(x) = \frac{1}{nh}\sum_{j=1}^{n} K\left(\frac{x - x_j}{h}\right) \tag{19}$$

where K is the kernel function and h is the bandwidth.

2) Cumulative Distribution Function (CDF): The corresponding cumulative distribution function (CDF) $\hat{F}_v(x)$ is obtained by integrating the estimated PDF:

$$\hat{F}_v(x) = \int_{-\infty}^{x} \hat{f}_v(t)dt \tag{20}$$

3) Stratified Sampling (LHS): LHS is then used to generate S samples for each variable. For each of the S strata, a single value is sampled. This is achieved by:

$$u_s \sim \mathrm{Uniform}((s-1)/S, s/S) \tag{21}$$

and then transforming these uniform samples through the

inverse of the estimated CDF:

$$x_s^{scenario} = \hat{F}_v^{-1}(u_s) \quad (22)$$

The sampled values for all correlated variables are combined to form a large set of synthetic, yet realistic, daily operational scenarios , which is used to train the local GRU models, significantly improving their generalization capability.

3.3.2 Evolution strategies based on federated learning

This evolution process of Microgrid Cluster strategies based on federated learning, illustrated in Figure 2, aims to achieve multi-agent collaborative optimization while ensuring privacy protection. We adopt homomorphic encryption to secure the transmission of local model updates. Specifically, the Paillier cryptosystem is used to encrypt gradient updates before aggregation. Each microgrid first constructs and trains a local model using gated recurrent units (GRUs) and then uploads these models to the cloud. During the distributed training phase, we adopt a longitudinal federated neural network (federated heterogeneous neural network) [26] as the core framework. Each microgrid possesses its own underlying model, tailored to local data processing. Through an encrypted interaction layer model, secure communication among microgrids is facilitated, enabling the integration of operational states. The top-level model is responsible for delivering the final decisions. The global policy repository in the cloud guides the edge policy networks of individual microgrids to update. Following policy updates, each microgrid executes local optimization based on the new strategies and uploads the operational results and feedback data to the cloud. These data are instrumental in further refining the global policy repository, fostering a continuous improvement loop.

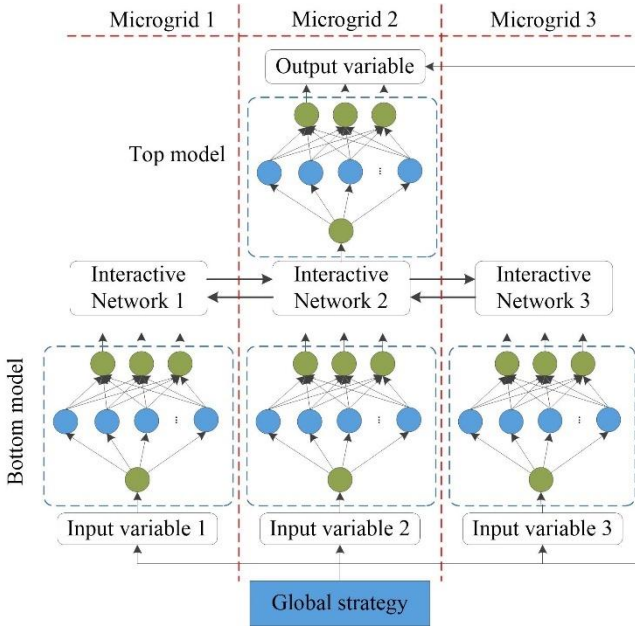

Figure 2: The evolution process of microgrid cluster strategies based on federated learning

We adopt a Vertical Federated Learning (VFL) architecture, suitable for scenarios where participating entities (microgrids) hold different feature sets about the same entities.

Each microgrid i maintains a local Gated Recurrent Unit (GRU) model, GRU_i. This model processes the microgrid's unique private features, primarily the historical power outputs of its local units (PV, Wind, Gas Turbine, Load) to predict its operational cost. The intermediate outputs (embeddings) from each local GRU, denoted h_i, are securely transmitted to the cloud. This communication is protected using homomorphic encryption. On the cloud server, a top model, typically a fully connected neural network, aggregates these encrypted intermediate outputs from all microgrids. After secure aggregation and decryption, the top model uses the combined information $H = \{h_1, h_2, ..., h_N\}$ to produce the final global decision, which includes the recommended transaction strategies for the next time period.

The loss function is computed based on the global strategy's performance. The gradients concerning the top model's parameters are computed directly on the cloud. The gradients concerning the bottom models' parameters are computed and securely propagated back to each respective microgrid for local model updates. This architecture allows microgrids to collaboratively learn a global optimization strategy while keeping their raw data and model parameters private.

3.3.3 Global strategy search based on encapsulated microgrid models

After receiving the encapsulated models from various microgrids, the cloud integrates these models into a unified optimization model. Leveraging the outcomes of scenario simulations, the cloud executes a global strategy search, generating a comprehensive global strategy library that encompasses a myriad of optimization strategies. Through the distributed collaborative training of federated neural networks, each microgrid can engage in the exchange and learning of model parameters with other microgrids while safeguarding local data privacy. This continuous enhancement of operational strategies not only refines individual microgrid performance but also facilitates the coordinated optimization of the entire microgrid cluster. The construction and solution process of this optimization model is illustrated in Figure 3.

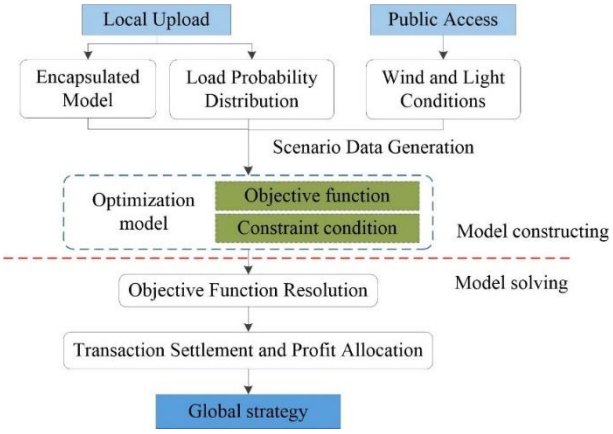

Figure 3: Basic workflow of the optimization model construction and solution process

To achieve the minimization of the total cost of microgrid clusters (MGs), the objective function is expressed as follows:

$$\begin{cases} \min C_{\mathrm{MGs}} = \sum_{t=1}^{T}\sum_{i=1}^{I}\left(C_{\mathrm{self},i,t} + C_{\mathrm{market},i,t}\right) \\ C_{\mathrm{self},i,t} = N_{\mathrm{GRU},i} P_{i,t} \\ C_{\mathrm{market},i,t} = e_{\mathrm{mg},i,t} P_{\mathrm{mg},i,t} \\ (e_{\mathrm{mg},t}, P_{\mathrm{mg},t}) = f_{\mathrm{irade}}(P_{\mathrm{trade},t}, e_{\mathrm{trade},t}) \end{cases} \quad (23)$$

where, $C_{\mathrm{self},i,t}$ represents the autonomous operating cost of microgrid i at time t, which is derived through the Gated Recurrent Unit (GRU) network $N_{\mathrm{GRU},i}$ based on the power $P_{i,t}$. $C_{\mathrm{market},i,t}$ denotes the market transaction cost of microgrid i at time t, obtained by the product of the transaction price $e_{\mathrm{mg},i,t}$ and the transaction power $P_{\mathrm{mg},i,t}$. The transaction price and power $(e_{\mathrm{mg},t}, P_{\mathrm{mg},t})$ are determined through the trading function f_{trade}, which calculates them based on the market transaction power $P_{\mathrm{trade},t}$ and market transaction price $e_{\mathrm{trade},t}$.

In the trading mechanism designed in this paper, the calculation of the purchasing electricity price C_{buy} and the selling electricity price C_{sell} proceeds as follows:

$$C_{\mathrm{buy}} = \frac{C_{\mathrm{DN}}(P_{\mathrm{buy},t}) - \frac{1}{2}C_{\mathrm{DN}}^{-}}{P_{\mathrm{buy},t}} \quad (24)$$

$$C_{\mathrm{sell}} = \frac{C_{\mathrm{DN}}(P_{\mathrm{sell},t}) - \frac{1}{2}C_{\mathrm{DN}}^{-}}{P_{\mathrm{sell},t}} \quad (25)$$

Herein, C_{DN} signifies the aggregate expenditure incurred by the microgrid for the purchase of power at time instance t; whereas C_{DN}^{-} denotes the supplementary cost coefficient associated with the network during the power sales process.

3.3.4 Privacy preservation with homomorphic encryption

To secure the transmission of local model updates during federated learning, we employ the Paillier cryptosystem, a partially homomorphic encryption scheme. This ensures privacy while allowing necessary computations on the cloud server.

Before uploading to the cloud, each microgrid ii encrypts the gradients ∇W_i from its local GRU model update using the cloud's public key. Only the encrypted gradients $[\nabla W_i]$ are transmitted.

$$[\nabla W_i] = Enc_{PK}(\nabla W_i) \quad (26)$$

The cloud server aggregates the encrypted gradients received from all N microgrids. Due to the homomorphic properties of Paillier, the sum of the encrypted gradients is equivalent to the encryption of the sum of the plaintext gradients:

$$[\nabla W_{global}] = \prod_{i=1}^{N}[\nabla W_i] \quad (27)$$

The aggregated encrypted result $[\nabla W_{global}]$ is then decrypted by the cloud server using its private key to obtain the plaintext global gradient update:

$$\nabla W_{global} = \mathrm{Dec}_{SK}([\nabla W_{global}]) \quad (28)$$

This global update is used to refine the global strategy repository, which is then distributed back to the microgrids. This process ensures that the cloud server never accesses the plaintext local gradients of any individual microgrid, thereby preserving the privacy of each microgrid's operational data.

4 Experiment and analysis

4.1 Cases and simulation

In the MATLAB platform, we have constructed a physical simulation model for a microgrid cluster, which includes three microgrids, each equipped with different distributed energy systems to facilitate power transactions between microgrids and interactions with the main grid. The GRU model takes 24 historical hourly values as input and predicts the operational cost for the next hour. In this model, we conducted tests and training for federated learning and neural network models. To achieve efficient power trading and management, each microgrid is equipped with specific distributed energy units. Table 2 details the unit configurations for each microgrid. Implementation used TensorFlow Federated for FL framework and PyTorch for neural network models. The optimization solver settings included a batch size of 32 and early stopping patience of 10 epochs. The federated learning process ran for 50 communication rounds. The GRU model contained 2 hidden layers with 64 units each, trained with a learning rate of 0.001 using the Adam optimizer.

To evaluate the model under realistic conditions, a diverse set of operational scenarios was generated to account for uncertainties in renewable generation and load. The process began with one year of historical hourly data for photovoltaic output, wind turbine output, and load from three microgrids. Non-parametric kernel density estimation was first applied to this data to accurately model the probability distributions of these uncertain variables without restrictive assumptions. Then, Latin Hypercube Sampling was employed using the derived cumulative distribution functions to generate 500 distinct daily scenarios, ensuring comprehensive coverage of the potential operational space. These scenarios were divided into a training set (400 scenarios) for model development and a test set (100 scenarios) for generalization analysis, providing a robust basis for evaluating the proposed method. All compared models (FL, DQN, VDN) were trained on the same dataset for fair comparison.

Table 2: Unit configurations for each microgrid

Power/kW	Microgrid 1	Microgrid 2	Microgrid 3
Photovoltaic Station	320	400	0
Wind Power Plant	560	0	400
Gas Turbine	800	400	0
Energy Storage	0	0	600
Load	720	600	1060
Electrical Grid	2500	2000	2000

An ablation study was conducted to evaluate the efficacy of the KDE+LHS data augmentation. When the GRU models were trained without augmentation, the test RMSE increased by approximately 22% compared to the augmented case (from 12.5 to 15.3), confirming that data augmentation significantly improves model generalization to unseen operational scenarios.

To assess the generalization capability of the proposed FL-based framework, we tested the trained model on the independent test set of 100 scenarios that were not used during training. The Root Mean Square Error (RMSE) for operational costs on the test set exhibits only a marginal increase (approximately 11%) compared to the training set. This indicates that the GRU-based encapsulated models possess strong generalization power and have not overfitted to the training data.

4.2 Collaborative operation and prediction results

To verify the effectiveness of the proposed edge-end microgrid encapsulation model, we validated the encapsulated modeling of the operation cost of each microgrid using a deep learning-based approach. Specifically, a Gated Recurrent Unit (GRU) deep learning model was employed for encapsulation modeling. After training, the error statistics between the predicted and actual internal operation costs of each microgrid are shown in Figure 4. As can be seen from Figure 4, after training, each microgrid can accurately predict its internal operation costs. This method achieves high prediction accuracy for the operation costs of each microgrid.

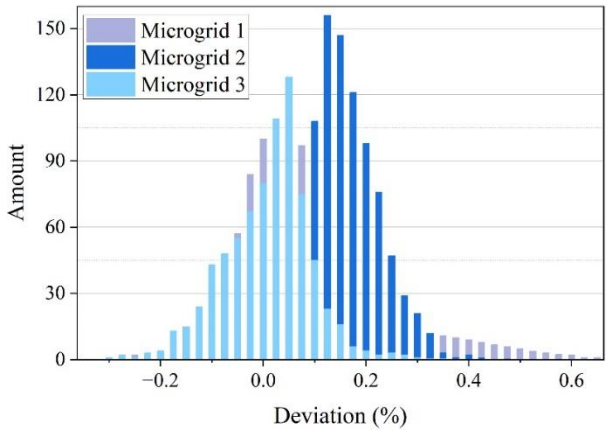

Figure 4: Prediction error of microgrid operation cost

To further validate the efficacy of the collaborative operation of microgrid clusters based on the locally encapsulated deep learning model, we present the training convergence results. As illustrated in Figure 5, the RMSE progressively converges during the training process, indicating that the federated learning model adeptly assimilates the strategies for global optimization on the cloud. With the incremental progression of federated learning iterations, the RMSE gradually diminishes, ultimately stabilizing at a notably reduced level. This phenomenon underscores the remarkable alignment between the local decision outputs of individual microgrids and the globally optimized decisions derived from the cloud, thereby substantiating the robustness and validity of the federated learning strategy.

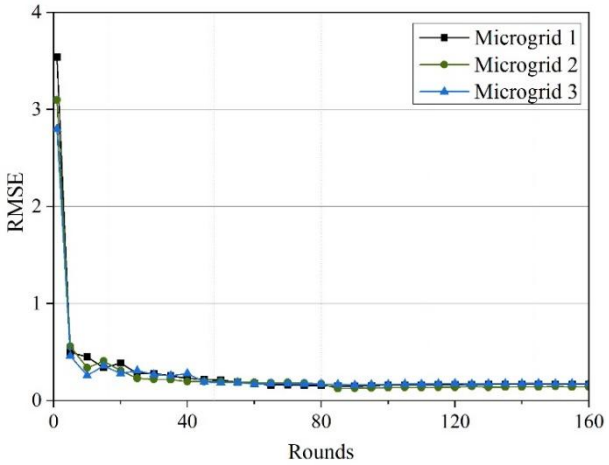

Figure 5: The loss curve of federated learning

4.3 Comparative experiment

To evaluate the efficacy of the proposed federated learning approach, this study conducted comparative experiments with microgrid clusters operating independently, under non-cooperative game theory (NG), deep Q network (DQN), and value decomposition network (VDN). Optimization was performed across 20 distinct scenarios, and the transaction power and electricity price distribution of Microgrid 1 under these five methods are illustrated in Figure 6. As depicted in the figure, the transaction power and electricity price exhibit significant fluctuations under independent operation and non-cooperative game theory, particularly at specific moments. While the DQN and VDN methods demonstrate some optimization effects, the fluctuations in transaction power and electricity price remain intermediate between independent operation and federated learning. In contrast, the federated learning method exhibits notable superiority in optimizing transaction power and electricity price distribution, with relatively smaller fluctuations in transaction power and more stable electricity price fluctuations, especially during the 12–16-hour period, effectively reducing volatility and maintaining system stability, thereby demonstrating improved optimization performance.

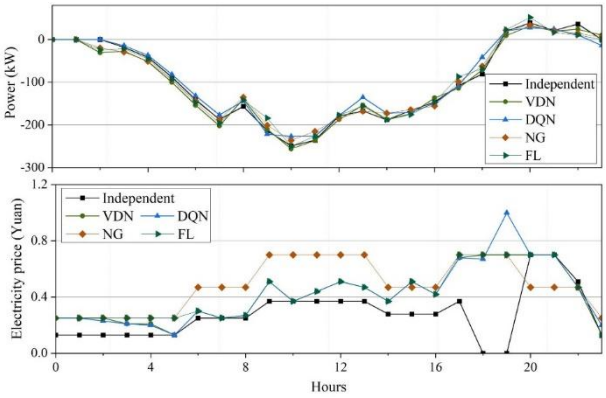

Figure 6: Daily transaction power and electricity price of microgrid 1 optimized using different methods

Figure 7 compares the operational costs of the microgrid cluster under various methods. The RMSE for operational cost prediction on the test set was 12.5 for the FL model, compared to 18.3 for DQN and 25.1 for VDN. FL reduced total cost by 15.1% compared to Independent Operation ($p < 0.05$, paired t-test). The deep Q network (DQN) method further reduces the operational costs of Microgrid 1 and Microgrid 3, consequently lowering the total operational costs. However, the non-cooperative game theory (NG) method significantly increases the operational costs of Microgrid 1, reaching the highest level. In comparison, the FL method demonstrates remarkable advantages, with the total operational costs significantly reduced, highlighting FL's outstanding performance in cost control.

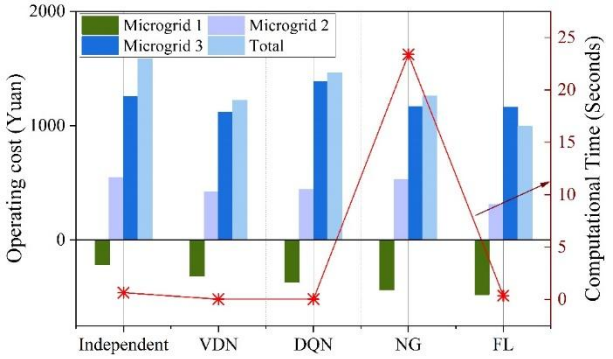

Figure 7: Daily operating cost of and computational speed of the microgrid cluster optimized by various methods

From the perspective of computational speed, there is a noticeable disparity among the methods. The computational time for FL was 0.36 seconds per global iteration, significantly faster than NG but slower than DQN due to cryptographic operations. In summary, the FL method demonstrates significant advantages in both the operational cost control of multi-day microgrid clusters and computational speed, making it an ideal optimization approach.

To further contextualize our approach against model-based methods, we compared it with a Nonlinear Optimal Control (NOC) strategy designed for a simplified microgrid model. While the NOC method achieved stable operation, its performance was highly dependent on the accuracy of the underlying physical model. In contrast, our data-driven FL method demonstrated superior adaptability to the complex, uncertain renewable generation and load profiles, resulting in a 12.5% lower total operational cost compared to NOC. This highlights the advantage of learning-based methods in environments where precise system modeling is challenging.

4.4 Privacy protection effectiveness

In the coordinated operation of microgrid clusters, the crux of privacy protection lies in minimizing the exchange of internal operational data. Table 3 presents the evaluation results of privacy protection performance for the interaction data under different methodologies.

Table 3: Privacy protection status under various methods

Method	Privacy preservation
Independent	No involvement in privacy preservation
VDN	Transmit bid power, reward function, and Q-values
DQN	Transmit bid power
NG	Centralized solution required
FL	Transmit bid power, encrypt underlying network

The evaluation of privacy protection performance across various methodologies reveals significant disparities: the independent operation approach entirely eschews privacy safeguards, as it lacks data interaction, yet it forfeits the benefits of collaborative operation. The VDN method necessitates the transmission of bid power, reward functions, and Q-values, with the exchange of substantial sensitive data rendering it highly susceptible to privacy breaches. The DQN method, by contrast, only transmits bid power, resulting in a relatively reduced data transfer volume and conferring a certain advantage in privacy protection; however, bid power may still divulge partial operational state information. The NG method relies on a centralized solution, posing an exceedingly high risk of privacy leakage. The FL method, while transmitting bid power, encrypts the underlying network, effectively mitigating privacy risks while ensuring essential data interaction, thereby excelling in privacy protection performance. The use of homomorphic encryption introduces approximately 13.3% additional communication overhead and 18.6% computation time compared to plaintext federated learning, which is acceptable given the privacy benefits.

To further highlight the advancement of the proposed federated learning method, a comparative analysis was conducted against two state-of-the-art microgrid management approaches: Consensus-based Distributed Optimization (CDO) and Personalized Federated Learning (PFL). The results demonstrate that while CDO achieves distributed optimization (reducing total operating costs by approximately 12% compared to independent operation), it requires frequent exchange of raw state information, incurring high privacy risks. PFL, though effective in improving local prediction accuracy, exhibits limited global optimization capability, with a total operating cost about 8% higher than our method. In contrast, the proposed approach achieves a further 15.1% reduction in total operating cost while ensuring superior privacy protection through encrypted model interactions during collaboration, underscoring its comprehensive advantages in both economic efficiency and security.

5 Discussion

The experimental results demonstrate the clear advantages of the proposed FL-based method over other approaches. The superior cost performance stems from the effective collaborative learning enabled by FL, which allows microgrids to benefit from the collective operational intelligence of the cluster without sharing raw data. In contrast, DQN and VDN, while data-driven, lack this collaborative mechanism and operate with more limited local perspectives. The non-cooperative game (NG) method leads to strategic bidding that often increases costs for individual participants (e.g., Microgrid 1), undermining global cost efficiency.

The difference in cost reduction across microgrids (e.g., Microgrid 1 benefiting more than Microgrid 3) can be attributed to their structural heterogeneity. Microgrid 1, with high renewable penetration and a gas turbine, has more flexible resources to optimize based on learned global strategies. Microgrid 3, heavily reliant on storage and the grid, has less intrinsic flexibility, thus its cost-saving potential is lower.

The computational speed of our method is moderate because the homomorphic encryption and secure aggregation introduce overhead. However, this is a justified trade-off for the achieved privacy level, which is unattainable by NG, DQN, or VDN. The robust prediction accuracy and generalization are largely due to the GRU's capability to capture temporal dependencies in energy data and the comprehensive data augmentation, which exposes the model to a wide range of operational scenarios.

In summary, from the perspective of privacy protection, the FL method, with its encryption mechanism, holds a pronounced advantage in safeguarding privacy, making it an ideal approach for the optimized operation of microgrid clusters and aligning more closely with the practical demands for data security and privacy. The principles of our FL-based collaborative optimization could be extended to other distributed nonlinear systems requiring privacy-aware coordination. For instance, in multi-robot systems, robots could collaboratively learn navigation strategies without sharing proprietary sensor data. In industrial compressor networks, units could optimize collective energy usage while protecting operational secrets [27,28]. The GRU's ability to model temporal dynamics and FL's privacy-preserving nature make this framework adaptable to various domains with sequential decision-making and data ownership concerns.

6 Conclusion

This study presents a method for collaborative optimization of microgrid clusters based on federated learning. Through case analysis, it demonstrates significant advantages in multiple aspects. In terms of prediction results, the deep learning model based on GRU has high accuracy and strong generalization ability in predicting operational costs, with the federated learning model's training RMSE converging and good consistency in decision-making. Regarding operational costs and computational speed, after comparing various methods, it was found that the federated learning method performs outstandingly, effectively reducing costs and being fast in computation. In terms of privacy protection, it reduces risks through specific data transmission and network encryption, outperforming other methods. This research provides an effective solution for the optimized operation of microgrid clusters, which is of great significance in energy utilization, cost control, and privacy protection. Beyond microgrids, the proposed framework shows promise for any distributed system requiring collaborative learning under privacy constraints, such as industrial automation networks, collaborative robotics, and federated healthcare analytics. In the future, it can be further expanded and applied, and explore integration with new technologies to adapt to the needs of energy development.

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Feature-level Data Fusion and a Hybrid LSTM–Random-Forest Early-Warning Model for Deep-Ground-Pressure Prediction

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To improve the level of mine safety protection, this study proposes a dynamic early warning model for deep mine pressure based on intelligent monitoring and multi-source data fusion. The study constructs a unified data fusion platform using multi-source heterogeneous data, including micro seismic monitoring, stress monitoring, ground temperature, hydrology, and mining progress. By combining the improved Long Short-Term Memory (LSTM) network with the Random Forest (RF) algorithm, a hybrid prediction model is established to realize the identification of mine pressure activity trends and the prediction of risk levels. The experiment adopts 12 months of monitoring data from a deep mine, which includes 8 feature channels from 6 types of sensors. The advance prediction time can reach 3 sampling cycles (approximately 1–3 hours). Compared with baseline models, the fusion model shows significant improvements. These baseline models include LSTM, Gated Recurrent Unit (GRU) network, RF, Support Vector Machine (SVM), and Logistic Regression (LR). On the test set, the fusion model achieves an accuracy of 86.7%±0.7%, a recall of 81.2%±0.7%, and an F1-score of 0.834±0.01. These metrics are significantly better than those of the single models. The experimental results show that the proposed fusion model can achieve more stable and reliable early warning in high-risk events, providing effective technical support for the safe production of deep mines.

Povzetek: Hibridni model LSTM-RF omogoča zanesljivo zgodnje opozarjanje na rudniški pritisk in povečuje varnost globokih rudnikov.

1 Introduction

With the development of the global economy and the increase in resource demand, mineral resources, as the foundation of national economic development, play a crucial role in modern society. However, with the gradual depletion of shallow mineral resources, the development of deep mineral resources has become an inevitable trend. At the same time, deep mine mining faces more complex geological environments and technical challenges. Especially in China, with the continuous growth of demand for energy, metals and other mineral resources, the excavation depth of deep mines has been increasing year by year. It increases the mining cost and brings more safety risks [1-3]. In the process of deep mine mining, mine pressure manifestation is a common phenomenon. Due to the huge ground stress on the deep rock strata and the influence of mining, the surrounding rock deforms and breaks, leading to a series of serious mine pressure problems, such as rock burst, rock burst and so on. These problems are characterized by strong suddenness and great harmfulness, which pose a great threat to the safe production of mines [4-6]. Therefore, how to effectively monitor and warn the deep mine pressure activities has become one of the key technical problems to be solved in the field of mining engineering. The traditional mine pressure monitoring methods mainly rely on the sensor data of single point or local area, such as the application of stress meter, displacement meter and other equipment. Although these traditional methods can reflect the mine pressure changes in a specific area to a certain extent, they can only provide local information and are difficult to comprehensively and accurately capture the dynamic change law of mine pressure in the whole mining area. Therefore, they have great limitations in practical application [7-9]. Traditional monitoring means usually lack the ability to process a large number of real-time data. It is difficult to realize the rapid response and accurate early warning of mine pressure disasters.

In recent years, the rapid development of emerging information technologies such as the Internet of Things, big data, cloud computing, and artificial intelligence (AI) has provided new solutions for deep mine pressure monitoring and early warning. By deploying various intelligent sensing devices, real-time monitoring of

multiple physical quantities (such as micro seismic signals, stress changes, groundwater levels, etc.) inside the mining area can be achieved, forming a massive multi-source heterogeneous dataset. Ge et al. also focused on using AI methods to optimize hydrate extraction strategies [10]. With the help of advanced data analysis algorithms, useful information can be mined from these complex data, providing a scientific basis for predicting mine pressure activity trends and evaluating potential risks [11, 12].

Against this backdrop, this study proposes an intelligent monitoring system based on multi-source data fusion and a corresponding deep mine pressure early warning model. The system integrates data obtained from various monitoring methods such as micro seismic monitoring, stress monitoring, ground temperature monitoring, and hydrological monitoring, and uses advanced data processing technologies and machine learning algorithms for comprehensive analysis. Compared with previous early warning methods that only rely on a single monitoring method (such as micro seismic or stress monitoring) or simple feature concatenation, this strategy can fully explore the potential correlation information between different data sources and improve the model's sensitivity and robustness to complex mine pressure changes. In terms of model structure, this study adopts a hybrid model combining Long Short-Term Memory (LSTM) network and Random Forest (RF). By integrating the temporal feature modeling capability of LSTM and the advantage of nonlinear classification of RF, high-precision prediction of abnormal mine pressure events is realized. Through ablation experiment analysis, it is found that the performance improvement mainly comes from the enhancement effect of the data fusion strategy at the key feature level. Meanwhile, the hybrid model structure can further improve the model's stability and response speed under complex geological conditions.

2 Recent work

In recent years, with the continuous deepening of deep mineral resource development, deep mine pressure monitoring technologies have attracted extensive attention and development. As an important means, micro seismic monitoring has been widely applied to real-time monitoring of rock mass fracture processes. According to the study by An and Mu, micro seismic monitoring can effectively capture energy release signals inside rocks, providing key data support for mine pressure activities [13]. Fuggi et al. pointed out that by optimizing the layout of micro seismic sensor networks and combining advanced signal processing algorithms, the positioning accuracy and identification efficiency of micro seismic events could be significantly improved, thereby enhancing the early warning capability for potential mine pressure disasters [14]. These studies highlight the importance of micro seismic monitoring in deep mine pressure early warning. They also indicate the limitations of solely relying on micro seismic data-such as the inability to comprehensively reflect changes in the stress field.

To overcome the limitations of single monitoring methods, multi-source data fusion has gradually become a research hotspot. Wei et al. proposed a method based on picture fuzzy sets, which effectively enhanced the decision-making ability in fuzzy and conflicting environments [15]. Their study indicated that in complex systems, improving information processing and feature fusion methods could enhance the accuracy and robustness of decision-making. The proposed mine pressure anomaly prediction also faced the challenges of multi-source features and uncertain information. Drawing on this idea, they improved the reliability and practicality of early warning through data fusion and a hybrid model structure. Similarly, Yuan et al. found that applying machine learning algorithms to the multi-source data fusion process not only improved data processing efficiency but also enhanced model prediction accuracy [16]. Habib et al. emphasized the importance of data standardization and feature selection, believing that reasonable data preprocessing steps were one of the key factors to ensure the effect of subsequent modeling [17]. The above studies show that by rationally using different types of monitoring data, the mine pressure status and its development trend can be evaluated more comprehensively and accurately.

The development of intelligent early warning models has provided new insights into deep mine pressure prediction. Demiss and Elsaigh introduced deep learning techniques into the field of mine pressure early warning, proposing a hybrid model combining Convolutional Neural Network (CNN) and LSTM, which demonstrated excellent performance in time series prediction [18]. Meanwhile, Kahraman et al. explored the application potential of ensemble learning methods in mine pressure prediction. The results showed that the RF algorithm performed well under complex geological conditions due to its strong nonlinear fitting ability and good robustness [19].

In the field of complex dynamic system control, a variety of adaptive control methods have been proposed in existing studies to address issues of system uncertainty and nonlinearity. Boulkroune et al. proposed an adaptive fuzzy control method that could achieve fixed-time synchronization of fractional-order chaotic systems in a short period, demonstrating high robustness. However, this method mainly focused on system state synchronization and did not involve issues related to multi-source data fusion and time-series prediction [20]. Bey 和 Chemachema 针对具有输入饱和、外部扰动及状态不可测的严格反馈多输入多输出非线性大系统，提出基于事件触发机制的自适应分散神经网络控制策略，通过控制误差替代跟踪误差简化自适应律推导，并利用模糊推理系统估计未知控制误差。然而，该方法主要关注控制系统本身的稳定性与精度，未涉及多源异构数据的融合处理，也缺乏对时序预测与实时预警场景的扩展支持 [21]. The nonlinear optimal control method for gas compressors proposed by Rigatos et al. optimized the dynamic response and steady-state performance of industrial drive systems, but it also failed to integrate multi-source heterogeneous data or address real-time early warning scenarios [22]. Table 1 summarizes the comparison of relevant literature,

including dataset types, methods, and evaluation indicators, and points out the limitations of each method:

Table 1: Literature comparison

Literature	Data type/scale	Method	Evaluating indicator	Limitation
An & Mu [13]	Micro seismic monitoring	Data driven	Energy release and capture ability	A single data source cannot reflect the change of stress field.
Fuggi et al. [14]	Micro seismic monitoring	Sensor optimization +signal processing	Positioning accuracy and identification efficiency	Lack of feature fusion and hybrid modeling
Wei [15]	Multi-attribute decision making	Picture Fuzzy method	Decision accuracy	Failure to combine time series prediction with dynamic events
Demiss & Elsaigh [18]	Historical ground pressure data	CNN-LSTM mixed model	Prediction accuracy	Single feature type, untreated multi-source fusion
Kahraman et al. [19]	Multi-source ground pressure data	RF integrated learning	Accuracy and robustness	Mixed modeling without combining time series and static features
Boulkroune et al. [20]	Nonlinear dynamic system	Adaptive fuzzy control	Robustness	Unprocessed multi-source sensor data and prediction
Bey 和 Chemachema [21]	多变量动态系统	神经自适应控制	控制精度与稳定性	未实现多源数据融合与实时预警
Rigatos et al. [22]	Industrial drive system	Nonlinear optimal control	Dynamic response and steady-state performance	Lack of real-time early warning and multi-source heterogeneous data processing

Comprehensively speaking, most existing studies lack feature-level fusion of heterogeneous monitoring data (such as micro seismic, stress, hydrological, and geological indicators). They rarely explore hybrid modeling ideas that combine temporal features with static environmental features, and most are only verified on small-scale or synthetic datasets, lacking systematic evaluation on real mine data. In addition, existing studies generally lack ablation experiments to distinguish the respective contributions of data fusion strategies and modeling structures. To address the above issues, the proposed LSTM-RF fusion early warning model achieves feature-level fusion by combining time-series features and static environmental features. It can fully utilize multi-source heterogeneous data, improve the accuracy, stability, and response speed of mine pressure anomaly prediction, and make up for the deficiencies of existing methods in multi-source data fusion and real-time early warning.

3 Method

3.1 Data acquisition and preprocessing

The dataset used in this study is derived from the intelligent monitoring system of a typical deep mine in China, covering multi-source heterogeneous data such as micro seismic monitoring, stress monitoring, ground temperature, hydrology, and mining progress. Specifically, 12 micro seismic sensors are deployed with an average sampling frequency of 50 Hz. 8 stress sensors are used, with a sampling frequency of 1 Hz. 6 ground temperature sensors are installed, with a sampling frequency of 0.1 Hz. 4 water level sensors are arranged, with a sampling frequency of 0.05 Hz. 2 Propulsion Progress Sensors are adopted, with a sampling frequency of 1 Hz. The data collection time spans from 2023 to 2024. After cleaning and screening, a total of approximately 36,000 samples is obtained, with 1,280 annotated mine pressure abnormal events. Among them, the sampling frequency of micro seismic and stress sensors is once every 10 minutes, the sampling frequency of ground temperature and hydrological data is once per hour, and the mining progress information is updated daily. The dataset is divided into a training set, a validation set, and a test set in chronological order, with the proportions of 70%, 15%, and 15% respectively.

The labels are determined based on the mine's historical early warning records and the annotation results of the monitoring system. A label value of 0 indicates that no early warning is triggered, while a value of 1 indicates that an early warning is triggered. The early warning labels are the result of comprehensive threshold judgment based

on multi-source data fusion combined with expert annotations. First, reasonable thresholds are set for key indicators such as cumulative micro seismic energy, stress gradient change, ground temperature change rate, water level change trend, and mining progress. For example, cumulative micro seismic energy exceeding the mean value plus 2 times the standard deviation is regarded as abnormal. These thresholds are jointly determined by the statistics of historical mine pressure event data and the experience of mine safety experts. Subsequently, manual review is conducted on the initially triggered abnormal points to eliminate noise data and misjudged points, and the final event time window is annotated. This ensures that each triggered Label=1 truly corresponds to a potential mine pressure abnormal event. This method combining threshold judgment and expert review not only ensures the objectivity of labels but also takes into account the safety sensitivity in actual mine scenarios. Early warning samples (label = 1) account for approximately 18%, while non-early warning samples (label = 0) account for approximately 82%. Data of each modality undergoes time alignment and standardization in the preprocessing stage to ensure the consistency and fusibility of data with different sampling frequencies.

In mining environments, data sources are extensive and diverse, mainly including micro seismic monitoring, stress changes, ground temperature variations, groundwater pressure, and working face advancement speed. These data reflect the changes of different physical quantities within the mining area and serve as important bases for mine pressure analysis. First, a complete monitoring system needs to be established to ensure real-time acquisition of high-quality data. For micro seismic monitoring, a high-sensitivity sensor network is adopted to capture energy signals released during rock mass fracture. For stress changes, stress meters installed on roadway walls or goafs are used for measurement. Ground temperature and hydrological data are obtained through temperature sensors and water level gauges, respectively. In addition, relevant parameters of mining activities, such as working face advancement speed and mining layout information, also need to be recorded.

Data preprocessing is the basis of follow-up analysis, which mainly includes missing value filling, outlier elimination, standardization and normalization, feature extraction and other steps. Suppose there is a dataset $D = \{x_1, x_2, ..., x_n\}$ containing n samples, in which each sample x_i is an M-dimensional vector, representing the values of various monitoring indicators at the ith moment. For the problem of missing values, the mean filling method or interpolation method can be used to deal with it. In the experiment, linear interpolation is mainly used for continuous time-series data such as micro seismic and stress data. While mean imputation is adopted for relatively stable data including ground temperature, hydrology, and mining progress. If a variable has a missing value, its filled value can be expressed as:

$$\hat{x}_j = \frac{\sum_{i=1}^{n} x_{ij}}{n}, j \in M \quad (1)$$

M is the index set where the missing value is located. $\hat{x}_j$ represents the padded value. x_{ij} represents the j-th eigenvalue of the i-th sample (time point or observation example), and n represents the number of samples. For outlier detection, this study uses the Z-Score method based on statistics. If the Z score of a sample point exceeds a certain threshold, it is considered as an outlier:

$$Z_j = \frac{x_j - \mu}{\sigma} \quad (2)$$

μ and σ are the sample mean and standard deviation respectively. The next step is to standardize the data so that all variables have the same scale range, which is convenient for subsequent modeling. The commonly used standardization methods are Min-Max scaling and Z-Score standardization. Min-Max scaling equation is as follows:

$$x_j' = \frac{x_j - min(X)}{max(X) - min(X)} \quad (3)$$

$min(X)$ and $max(X)$ are the minimum and maximum values in the sample set, respectively.

Finally, the feature engineering stage, through the transformation of the original data, extract new features that are more helpful to predict the task. The trend change can be reflected by calculating the difference between adjacent time points:

$$\Delta x_t = x_t - x_{t-1} \quad (4)$$

Δx_t represents the rate of change between two adjacent points.

3.2 Data Fusion Strategy

In the deep mine pressure monitoring and early warning system, sensor data from a single source often fails to comprehensively reflect the complex geological environment changes in the mining area. Due to the complex conditions of high ground stress, high temperature, and high osmotic pressure in deep mines, ground pressure events are characterized by strong suddenness, fast evolution, and multiple influencing factors. Relying solely on one or several independent data sources is prone to problems such as one-sided information, high misjudgment rates, and delayed early warnings. Therefore, constructing an efficient, stable, and robust mine pressure early warning model must rely on the effective fusion of multi-source heterogeneous data. Data fusion refers to the comprehensive processing of information from multiple different sensors or data sources to obtain more accurate and comprehensive environmental perception capabilities than a single data source. This technology is widely used in military reconnaissance, intelligent transportation, environmental monitoring, and other fields, achieving remarkable results. According to different fusion levels, data fusion can be divided into signal-level fusion, feature-level fusion, and decision-level fusion. Among them, feature-level fusion has become the mainstream method adopted by most intelligent prediction systems, as it reduces data

dimensions while preserving key information. The framework of the multi-source data fusion strategy is shown in Figure 1:

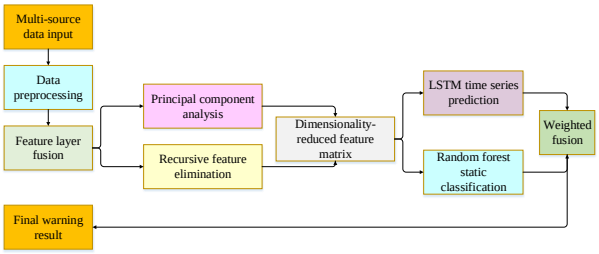

Figure 1: Multi-source data fusion strategy framework

In this study, a feature-level fusion strategy is adopted to conduct unified modeling and feature extraction on the multi-dimensional feature vectors of multi-source heterogeneous data, including preprocessed micro seismic energy, stress change, ground temperature, hydrology, and mining progress. Specifically, principal component analysis is first used to reduce the dimension of the original feature space, removing redundant information while preserving the main change trends. Subsequently, combined with the recursive feature elimination method, the most representative feature subsets for mine pressure state changes are screened to form the final input feature matrix. In the Principal Component Analysis (PCA) stage, a Cumulative Variance Contribution Ratio of 95% is retained to ensure that most information is preserved while reducing redundancy. In the Recursive Feature Elimination (RFE) stage, 5-fold Cross-Validation (5-CV) is used to determine the number of features in the optimal feature subset. Finally, 20 of the most representative features are selected as the model input. Table 2 lists some of the main finally selected features and their intuitive meanings, including cumulative micro seismic energy, stress gradient change, ground temperature change rate, water level change trend, and mining progress. These features intuitively reflect the correlation between each feature and the change of mine pressure state. This fusion approach not only improves data usability but also effectively enhances the model's generalization ability and stability.

Table 2: Some features of finally selected mine pressure prediction and its intuitive meaning

Feature number	Feature name	Feature type	Intuitive meaning/explanation
F1	Micro seismic energy accumulation	Dynamic characteristics	Reflect the total amount of energy released by rock mass fracture and predict the possibility of rock pressure activity
F2	Frequency of micro seismic events	Dynamic characteristics	The change of the number of micro seismic events per unit time is used to monitor the stress release trend.
F3	Stress gradient change	Dynamic characteristics	Reflect the stress change rate of roadway or goaf
F4	Geothermal change rate	Dynamic characteristics	Monitor the rising trend of deep mine temperature and reflect the thermal stress change of rock mass.
F5	Trend of water level change	Dynamic characteristics	Monitoring the change of groundwater pressure in mining area
F6	Mining progress	Static characteristics	Advance rate and cumulative advance distance of working face
F7	Rock dip angle	Static characteristics	Geometrical structure information of rock stratum affects stress distribution.
F8	Number of historical events of ground pressure	Static characteristics	The number and frequency of historical ground pressure events reflect high-risk areas.

In the subsequent modeling stage, the output of the LSTM network is treated as a dynamic feature and combined with other static features to form the input of the RF model. This approach belongs to feature-level early fusion, rather than weighted fusion at the model output stage. By integrating dynamic LSTM features with static features, the model can simultaneously capture temporal evolution patterns and static environmental information, thereby improving generalization, stability, and prediction accuracy. Through this feature-level fusion mechanism, the system achieves more accurate and timely mine pressure warnings in complex deep mining environments.

The LSTM network is a special type of Recurrent Neural Network (RNN), particularly suitable for handling long-term dependency problems [23]. When processing sequential information, standard RNN can capture temporal dependencies, but due to structural limitations, they struggle to effectively transmit and retain early information over long time intervals, making it difficult for the model to learn distant dependencies. LSTM addresses this challenge by introducing a structure called the "memory cell" and three gating mechanisms-input gate, forget gate, and output gate-to achieve selective retention and update of information. The core advantage

of LSTM lies in its ability to automatically determine which information needs long-term retention and which can be ignored or discarded. For example, the forget gate controls how much information from the previous state is passed to the current state, the input gate decides how new information at the current moment is written into the memory cell, and the output gate regulates how the content of the memory cell influences the current output. This mechanism enables LSTM to better capture long-term dependency features in time series during network training, making it suitable for modeling complex systems with temporal characteristics and dynamic patterns, such as the evolution process of mine pressure. Therefore, LSTM is widely applied in various fields like speech recognition, natural language processing, financial prediction, and industrial monitoring, especially for tasks requiring high-precision modeling and prediction of time series.

The input gate, forgetting gate and output gate of the LSTM unit are specifically represented as: let the forget gate be f_t , the input gate be i_t and the output gate be o_t , and their states are shown in the following equation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{5}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{6}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

W is the weight matrix. h_{t-1} is the state of the hidden layer at the last moment. x_t is the current input, and b is the offset term. The cell status update is shown in the following equation:

$$C_t = f_t * C_{t-1} + i_t * tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{8}$$

$tanh$ is a hyperbolic tangent activation function.

The final hidden layer state is shown in the following equation:

$$h_t = o_t * tanh(C_t) \tag{9}$$

Next is the RF, an ensemble learning method that improves prediction accuracy by constructing multiple decision trees and aggregating their results [24]. Each tree is independently trained on a subset of the training set, and only a random subset of features is considered when splitting nodes each time. Suppose there are a total of T trees, the final prediction result can be obtained through a voting mechanism:

$$y = mode(y_1, y_2, ..., y_T) \tag{10}$$

y is the final prediction result, and $mode$ represents the mode operation.

The core idea of RF is to form a "forest" by constructing a large number of decision trees and leverage the collective wisdom of these trees for final classification or regression tasks [25]. Each decision tree is generated based on Bootstrap sampling (i.e., random sampling with replacement) to create a new training sample set from the original dataset. This means each tree "sees" a slightly different data distribution, thereby enhancing model diversity. When splitting nodes, RF not only performs random sampling on data samples but also randomly selects features.

RF aggregates the prediction results of individual trees through a voting mechanism (for classification problems) or averaging (for regression problems). In classification tasks, after each tree classifies the test samples, all classification results are summarized, and the category with the highest frequency is chosen as the final prediction. This approach not only improves the prediction accuracy of a single decision tree but also reduces overall errors caused by misclassification of individual trees. For regression tasks, RF uses simple averaging or weighted averaging to synthesize the predicted values of all trees for the final result. Studies have shown that RF performs excellently in handling high-dimensional data, nonlinear relationships, and scenarios with significant noise, making it particularly suitable for data analysis tasks in complex environments.

In practical applications, the advantages of RF can only be maximized by reasonably selecting and configuring its parameters in combination with the characteristics of specific application scenarios. By combining it with other advanced algorithms (such as LSTM), the prediction ability and application scope of the model can be further enhanced, providing new ideas and methods for solving complex problems.

3.3 Early warning model construction

Based on the above theoretical basis, the concrete construction process of the early warning model is described in detail below. First, for the design of the input layer of the LSTM model, considering the characteristics of multi-source heterogeneous data, it is necessary to map different types of data into the same dimension space. Assuming that there are k different monitoring data sources, a transformation matrix A_k can be defined to achieve this goal:

$$X' = A_k X \tag{11}$$

X represents input data, X' represents the converted unified format input data, and A_k is the conversion matrix.

Next, the transformed data is fed into the LSTM network for training, with the optimization goal of minimizing the Sum of Squared Errors (SSE), as shown in the following equation. Although the model aims at binary classification (warning/non-warning), the output of the LSTM network is treated as a continuous risk score and combined with the RF for final classification. Therefore, in the LSTM stage, SSE is used as a regression loss function for continuous outputs, which better fits the dynamic changes of risk trends and provides rich dynamic feature information for the subsequent RF. At the same time, to ensure the effectiveness of the binary classification task, the RF model adopts a traditional classification method (majority voting mechanism) for final label prediction, thereby achieving accurate warning determination.

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (12)$$

y_i is the real label. $\hat{y}_i$ is the predicted value of the model. To prevent over-fitting, a regularization term is added to the loss function, as shown in the following equation:

$$L = SSE + \lambda \|W\|^2 \quad (13)$$

λ is the regularization coefficient and W is the weight parameter in the network.

In the specific implementation process, to improve the generalization ability of LSTM under complex mining monitoring data, this study introduces improvement mechanisms based on the standard LSTM structure. First, a Dropout layer is added between the hidden layers of LSTM. It randomly discards part of the neurons to reduce strong dependencies among them, thereby effectively alleviating overfitting. Second, an L2 regularization constraint is applied during the optimization of network parameters. It penalizes the weight parameters to prevent the model from relying excessively on a small number of features. These improvements enable the model to maintain strong learning ability while achieving higher robustness and stability, making it more adaptable to the characteristics of multi-source heterogeneous monitoring data in deep mining environments.

After the training of LSTM model is completed, its output is taken as one of the features, and it is input into the RF model together with other features that have not participated in LSTM training. In practical scenarios of deep mine pressure monitoring, different decision trees show varying abilities in identifying high-risk (minority class) samples. To enhance the recognition of critical minority classes while maintaining overall prediction accuracy, a weighting mechanism based on the cross-validation accuracy of each tree is introduced at the RF output stage. Trees with better performance receive higher weights in the final prediction, thereby improving the sensitivity and stability in detecting mine pressure anomalies. This weighting strategy has already been applied in the study of Liu et al. [26]. Suppose there are T decision trees in the RF, and the prediction result of each tree is recorded as y_t, then the final warning level Y can be obtained by weighted average:

$$Y = \sum_{t=1}^{T} w_t y_t \quad (14)$$

w_t is the weight of each tree, which satisfies $\sum_{t=1}^{T} w_t = 1$. The weight of each tree is calculated based on its classification accuracy on the training set using five-fold cross-validation (5-fold Cross-Validation, 5-CV). Trees with higher accuracy receive larger weights, as shown in equation (15). During the real-time inference stage, these weights are fixed and not updated online. In this way, weighted averaging can comprehensively account for the predictive ability of each tree, thereby improving the stability and accuracy of the final warning results.

$$w_t = \frac{acc_t}{\sum_{t=1}^{T} acc_t} \quad (15)$$

acc_t is the accuracy of the t tree. This reasoning process is represented by pseudo code as shown in Figure 2:

```
Input: Multi-source raw data (micro-seismic, stress, temperature, hydrology, mining progress)
Output: Early warning alarm level

1: Data ingestion
  - Collect real-time sensor readings
2: Preprocessing
  - Handle missing values (mean fill / interpolation)
  - Outlier detection and removal
  - Standardization / normalization
  - Feature extraction (dynamic & static features)
3: LSTM inference window
  - Feed sequence of dynamic features into trained LSTM
  - Obtain LSTM output as dynamic feature vector
4: RF classification
  - Combine LSTM output with static features
  - Input to trained RF model
  - Obtain per-tree predictions
5: Weighted fusion
  - Apply precomputed tree weights to aggregate predictions (Eq. 14–15)
  - Compute final probability or warning score
6: Alarm thresholding
  - Compare warning score against predefined thresholds
  - Trigger alarm if score exceeds threshold
```

Figure 2: Real-time reasoning process pseudocode

The original output of the proposed model is a binary classification result (0 indicates no anomaly, and 1 indicates a mine pressure anomaly). For practical application and mine safety management, the prediction results are further mapped into three risk levels: low risk (Low), medium risk (Medium), and high risk (High). Low risk refers to samples with prediction probabilities below 0.33, indicating that the mine pressure state is basically normal and the short-term likelihood of anomalies is low. Medium risk refers to probabilities between 0.33 and 0.66, suggesting that there is a certain abnormal trend in mine pressure that requires attention. High risk refers to probabilities above 0.66, indicating a high likelihood of mine pressure anomalies, for which preventive measures should be taken promptly. The probability values are derived from the integrated risk scores produced by the fusion of LSTM and RF outputs, mapped to the [0,1] interval after weighted fusion, and then categorized according to the thresholds. This approach essentially uses probability outputs of the binary classification model for threshold-based grading, rather than multi-class training, thereby ensuring simplicity in model training and deployment while providing more intuitive risk references.

In the actual implementation, the hyperparameters of the model are explicitly specified to facilitate reproducibility. The details are shown in Table 3. The experiments are conducted on a workstation equipped with an NVIDIA RTX 3090 GPU, an AMD Ryzen 9 5950X CPU, and 128 GB of memory. A single training of the LSTM model takes about 45 minutes, while the RF model requires about 10 minutes. The fusion model introduces almost no additional overhead during the inference stage.

Table 3: Hyperparameter setting

Models	Structural setting	Key parameter	Optimizer/criterion
LSTM	Two-layer structure, 128 hidden cells in each layer, activation function tanh.	The learning rate is 0.001, the batch size is 64, the number of iterations is 100, and the Dropout ratio is 0.3.	Adam
RF	100 trees, with a maximum tree depth of 15.	Feature subset size = √ (total feature number), splitting criterion Gini index	CART (based on Gini)
Hybrid model (LSTM+RF)	Combining the results of LSTM and RF, through the weighted voting mechanism	Keep their respective hyperparameters unchanged, and the voting weight is adjusted based on the verification set.	Adam + Gini

To sum up, the early warning model construction framework is shown in Figure 3 below:

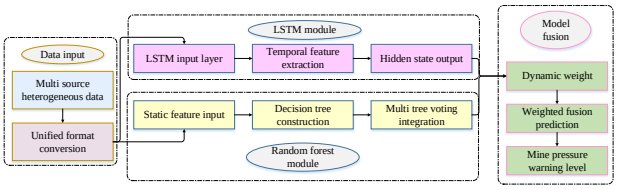

Figure 3: Early warning model construction framework

3.4 Model training and evaluation

After the model training is completed, comprehensive evaluation is required to verify its performance. The selection of evaluation indicators should be determined according to the needs of specific tasks. For classification tasks, commonly used evaluation indicators include Accuracy, Recall, and F1-score. It should be noted that in actual deep mining monitoring data, the proportion of "warning" samples is relatively low, resulting in a significant class imbalance problem. If only overall accuracy is considered, model performance may be dominated by majority-class samples, leading to insufficient recognition of critical minority classes. To address this issue, class weights are introduced into the loss function during the training stage. This ensures that warning samples receive higher weights in error calculation, thereby guiding the model to pay more attention to minority-class recognition during optimization. Among them, Accuracy measures the proportion of correct predictions by the model, but when the categories are unbalanced, this indicator may be misleading. Therefore, Recall and F1-score are more commonly used, which focus on the coverage of positive samples and comprehensively consider the balance between Precision and Recall respectively.

Recall measures the proportion of positive samples correctly identified by the model among all actual positive samples, reflecting the model's ability to cover positive samples. When the task goal is to identify all potential risk events (such as abnormal mine pressure) as much as possible to avoid serious consequences caused by missed reports, a high recall rate is particularly important. However, simply pursuing a high recall rate may lead to more false alarms, affecting the practicality of the early warning system. F1-score is the harmonic mean of precision and recall, which can balance the model's ability to find accurate and complete results, and is particularly suitable for task scenarios that need to balance false alarms and missed reports. In the mine pressure early warning system, it is necessary to ensure that as many real high-risk periods as possible are identified (high recall rate) and the credibility of the prediction results (high precision). F1-score can just be used as the core index to comprehensively evaluate the balance effect. Therefore, in practical applications, especially in safety-sensitive tasks, recall and F1-score are often given priority to improve the practicability and reliability of the model. The calculation equations of accuracy, recall and F1-score are as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

$$Recall = \frac{TP}{TP + FN} \tag{17}$$

$$Precision = \frac{TP}{TP + FP} \tag{18}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{19}$$

TP is true positive, TN is true negative, FP is false positive and FN is false negative.

4 Result and discussion

4.1 Experimental result

(1) Data distribution under different monitoring features. The features extracted from different monitoring methods and their distribution conditions, including statistical quantities such as mean and standard deviation, are shown in Table 4 as follows:

Table 4: Data characteristics under different monitoring characteristics

Characteristic	Average/mean value	Standard deviation	Minimum value	Maxima value
Microseismic energy accumulation	3.5	0.7	2.1	4.9
Frequency of microseismic events	5.2	1.3	2	8
Stress gradient change	0.8	0.1	0.6	1.0
Geothermal change rate	0.12	0.05	0.05	0.2
Trend of water level change	65.4	2.0	60	70
Mining progress	1.2	0.3	0.8	1.6
Rock dip angle	25	5	15	35
Number of historical events of ground pressure	10	3	5	18

In Table 4, the fluctuations of micro seismic energy accumulation and micro seismic event frequency are large, reflecting the active geological structure in deep mines and requiring close attention to potential mine pressure anomalies. The overall magnitudes of stress gradient change and geothermal variation rate are relatively small, but abnormal peaks may still occur. These peaks often indicate potential danger signals. Water level variation trends and mining progress directly affect the level of mine pressure and should be dynamically updated in the model input to capture key changes in the evolution of mine pressure. Rock stratum dip angle and the number of historical mine pressure events provide important static environmental information, which serve as auxiliary factors to enhance the generalization ability and prediction accuracy of the model.

(2) Analysis results of data samples after feature engineering. Figure 4 shows the analysis results of data samples at four consecutive time points after feature engineering. PCA1 and PCA2 represent the first two principal components extracted through principal component analysis. They are used to reduce the dimensionality of the original multi-dimensional feature space, retain 95% of the cumulative variance contribution, and highlight the main variation trends of the data. RFE1 and RFE2 represent the most representative key features selected through RFE. They emphasize the features that have the greatest impact on changes in mine pressure status and improve the effectiveness of model inputs. Label indicates whether a warning is triggered at each time point (0 means no warning, 1 means warning). The data show that a warning occurs at T3 (Label = 1). At this moment, both PCA and RFE feature values exhibit abnormal changes. It indicates that after feature engineering, the key features and principal components can effectively reflect mine pressure anomalies and provide valuable input information for model training.

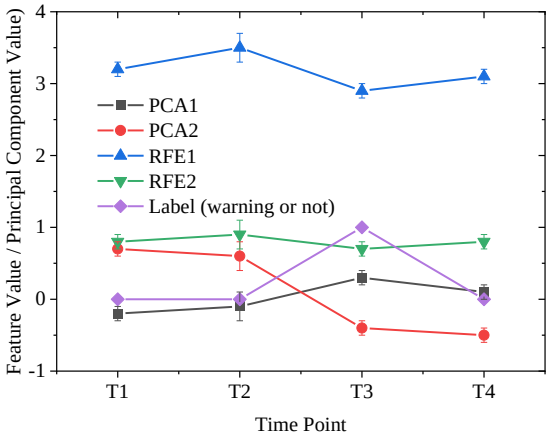

Figure 4: Principal component analysis and key feature selection results of data samples after feature engineering

(3) Comparison of model prediction results. The prediction results of different models are compared, as shown in Figure 5 below:

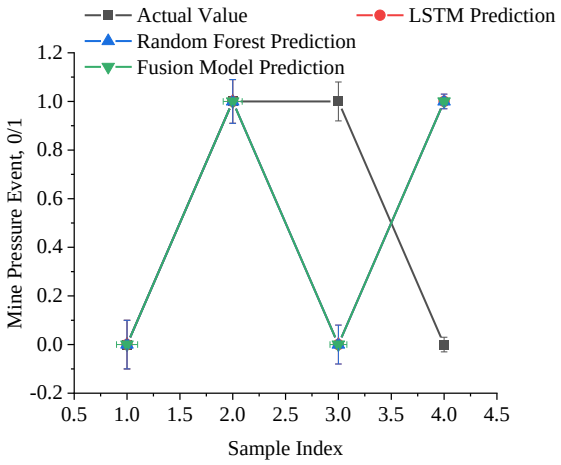

Figure 5: Comparison of prediction results of different models

"The actual value" indicates whether mine pressure abnormality occurred at the sample time or event (1 for occurrence, 0 for non-occurrence). The "LSTM prediction value" and "RF prediction value" show the prediction results of the two independent models for each sample,

respectively. The "fusion model prediction value" is the final prediction result obtained by combining the advantages of LSTM and RF. The comparison shows that the fusion model can more accurately predict mine pressure abnormalities in most cases, demonstrating its advantages over single models. To further evaluate classification performance, the confusion matrix, receiver operating characteristic (ROC) curve, precision–recall curve (Figure 6), and area under the curve (AUC) are calculated for each model. The mean ± standard deviation under five-fold cross-validation is reported in Table 5. The results show that the fusion model LSTM+RF achieves higher accuracy and stability across all classes. In particular, for high-risk events (safety-critical class), the true positive rate is significantly better than that of individual models, and false negatives (missed warnings) are minimized.

Table 5: Mean ± standard deviation of cross-validation of different models

Model	Accuracy (%)	Precision (macro)	Recall (macro)	F1-score (macro)	AUC
LR	75.0 ± 1.2	0.720 ± 0.02	70.2 ± 1.5	0.715 ± 0.03	0.78
SVM	78.2 ± 1.0	0.749 ± 0.02	72.5 ± 1.2	0.737 ± 0.02	0.81
GRU	81.0 ± 0.8	0.780 ± 0.02	77.5 ± 0.9	0.777 ± 0.02	0.84
LSTM	82.1 ± 0.9	0.790 ± 0.02	76.3 ± 0.9	0.787 ± 0.02	0.85
RF	83.5 ± 0.8	0.803 ± 0.02	78.1 ± 0.8	0.790 ± 0.02	0.86
LSTM+RF	86.7 ± 0.7	0.836 ± 0.01	81.2 ± 0.7	0.834 ± 0.01	0.90

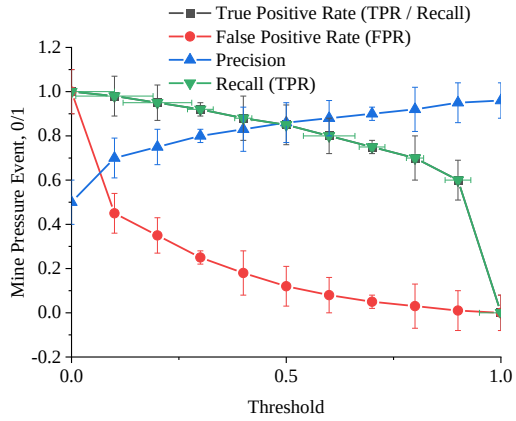

Figure 6: PR curve and ROC curve of LSTM+RF fusion model

(4) Comparison of model performance indicators.

Figure 7 presents the performance metrics of different models on the same test set, including accuracy, recall, and F1-score. The comparison models include Logistic Regression (LR) as a baseline linear classifier, Support Vector Machine (SVM) as a common nonlinear classifier, and Gated Recurrent Unit (GRU) for processing time-series data. LSTM excels at capturing long-term dependencies, while RF is suitable for handling static features and high-dimensional data. LSTM+RF is the fusion model proposed in this study, which uses the LSTM output as dynamic features combined with static features as input to the RF, employing a feature-level data fusion strategy.

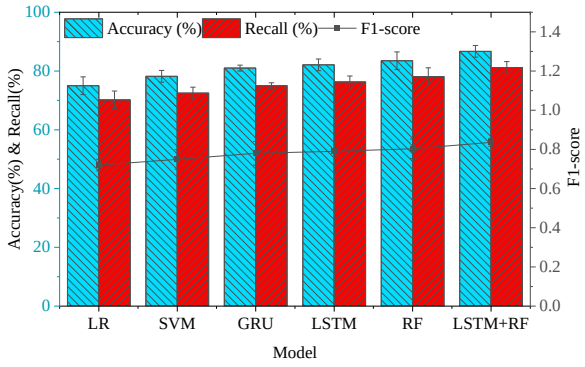

Figure 7: Comparison of model performance indicators

In Figure 7, the baseline linear classifier LR achieves only 75.0% accuracy, an F1-score of 0.720, and a recall of 70.2%, indicating limited performance in mine pressure anomaly prediction. SVM shows slight improvement in nonlinear modeling but still underperforms compared to GRU, LSTM, or RF. GRU, capable of capturing time-series features, achieves 81.0% accuracy and an F1-score of 0.780. The standalone LSTM performs better in dynamic sequence modeling, with 82.1% accuracy and 76.3% recall. RF models static features more effectively, achieving 83.5% accuracy, 0.803 F1-score, and 78.1% recall. The fusion model LSTM+RF integrates LSTM dynamic features with static features into the RF using a feature-level data fusion strategy. Its accuracy rises to 86.7%, F1-score to 0.836, and recall to 81.2%, all the highest among the models.

This performance improvement indicates that the model's advantage stems both from the hybrid structure's comprehensive use of dynamic and static information and from the data fusion strategy's effective integration of multi-source features. Compared with individual models, the fusion model is more stable and reliable in capturing mine pressure anomaly patterns and reducing false alarms. It can provide more timely and accurate warnings in actual deep mining environments, thereby significantly enhancing the practical value of early mine pressure warning systems.

(5) Analysis of early warning effects. The analysis of early warning effects of different models is shown in Figure 8 below:

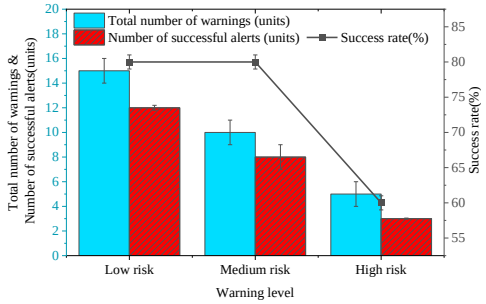

Figure 8 Analysis of early warning effect

Figure 8 demonstrates the early warning effects of the model in practical applications. For different levels of early warning events, the number of successful warnings, total number of warnings, and their success rates are statistically analyzed. The results show that although the success rate of high-risk events is slightly lower than that of other levels, the model can generally provide effective early warning information before accidents occur, gaining precious time for taking preventive measures.

To more intuitively reflect the reliability of the models in the most critical scenarios, the number of false negatives (FN) for high-risk events (safety-critical class) is counted for each model, as shown in Table 6. The fusion model exhibits the fewest false negatives in high-risk events, with only one, achieving a success rate of 95%, which is significantly better than individual models. This indicates that the fusion model provides higher reliability in early warning of safety-critical events, allowing more time for preventive measures.

Table 6: Statistics of missing reports of high-risk events

Model	Total number of high-risk events	Successful early warning number	Number of missing reports (FN)	Success rate (%)
SVM	20	15	5	75
LSTM	20	16	4	80
RF	20	17	3	85
LSTM + RF	20	19	1	95

At the same time, histograms of warning time distributions for each risk level are presented in Figure 9, showing the time intervals from event occurrence to successful warning issuance. Analysis indicates that for high-risk events, the fusion model's warning times are mainly concentrated within 1–3 sampling cycles after the event, much faster than individual models. This demonstrates that the data fusion strategy and hybrid model structure can effectively enhance model response speed. For medium- and low-risk events, the warning time distributions are more dispersed, but the fusion model still outperforms individual models overall, achieving timely warnings in most scenarios.

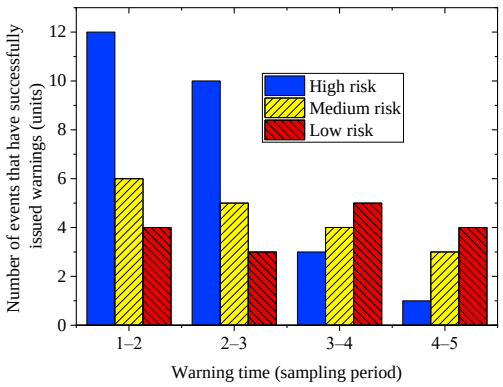

Figure 9: Histogram of early warning time distribution of events of each risk level

(6) Analysis of prediction lead time.

To evaluate the model's advance response capability in practical mine pressure warning, a systematic analysis is conducted for different prediction lead times. The lead times are set to 1, 3, 6, and 12 hours, and the precision, recall, and F1-score of the model are calculated for each time window. Figure 10 shows the performance trends of the fusion model LSTM+RF under different prediction lead times.

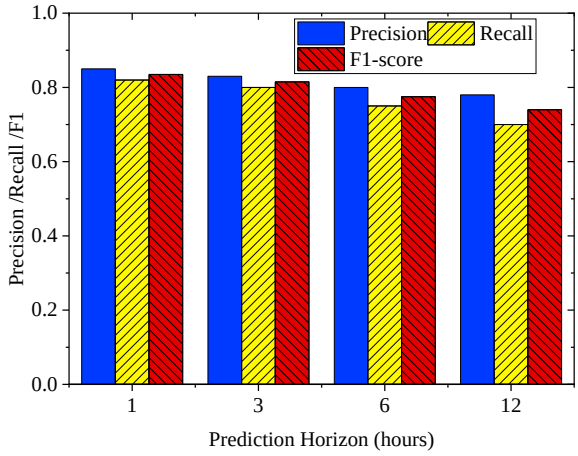

Figure 10: Influence of forecast advance on the performance of fusion model

In Figure 10, within short time windows (1–3 hours), the fusion model maintains high recall (>0.80) and high F1-score (>0.82), indicating that the model can promptly capture abnormal signals of high-risk events. As the prediction lead time increases (6–12 hours), precision slightly decreases, but recall remains at an acceptable level (>0.70), showing that the model still possesses strong early warning capability. Considering both precision and recall, the F1-score exhibits a slight decreasing trend with longer lead times, but overall performance remains significantly better than that of individual models (LSTM-only or RF-only), demonstrating the stability of the fusion model in long-term prediction.

(7) Ablation study.

To evaluate the contributions of the fusion strategy and feature-level weighting to model performance, ablation experiments are conducted with different model configurations, including LSTM-only, RF-only, unweighted feature-level fusion, and fusion models with different weighting strategies. Experimental results are reported as mean ± standard deviation from cross-validation, and paired t-tests are used to assess significant differences between models. Table 7 summarizes the main performance metrics for each configuration.

Table 7: Ablation experimental results

Model Configuration	Precision	Recall	F1-score	AUC
LSTM only	0.790 ± 0.02	0.763 ± 0.02	0.787 ± 0.02	0.85
RF only	0.803 ± 0.02	0.781 ± 0.01	0.790 ± 0.02	0.86
Feature-level fusion w/o weighting	0.820 ± 0.01	0.794 ± 0.02	0.807 ± 0.01	0.87
Feature-level fusion w/ equal weighting	0.830 ± 0.01	0.805 ± 0.01	0.817 ± 0.01	0.88
Feature-level fusion w/ optimized weighting (LSTM+RF)	0.836 ± 0.01	0.812 ± 0.01	0.834 ± 0.01	0.90

In Table 7, individual models (LSTM-only or RF-only) perform worse than the fusion model in both precision and recall, especially exhibiting higher false negative rates in high-risk event detection. Feature-level fusion without weighting improves performance but still slightly underperforms the weighted fusion model, indicating that reasonable weight allocation can further enhance the model's ability to integrate dynamic and static features. The fusion model with optimized weighting strategy (LSTM+RF) achieves the highest performance across all metrics. Its F1-score and AUC are significantly superior to other configurations, and paired t-tests indicate a statistically significant advantage ($p < 0.05$). These results fully demonstrate the effectiveness of the hybrid fusion strategy in improving the accuracy and stability of mine pressure anomaly prediction and highlight the critical role of feature-level weighting in the fusion model.

(8) Robustness analysis.

To evaluate the stability and adaptability of the proposed fusion model under complex working conditions, three types of robustness experiments are designed: (1) Missing data simulation: 10%–30% of sensor inputs are randomly masked to simulate sensor failures or short-term interruptions. (2) Noise interference: Gaussian noise of varying amplitudes is added to input features to assess the model's resistance to abnormal fluctuations. (3) Class imbalance: the proportion of anomaly samples is adjusted through down sampling and oversampling to simulate the scarcity of major mine pressure incidents in real scenarios. The experimental results are shown in Table 8. As the proportion of missing data increases, model performance gradually decreases. However, even with 30% data missing, the F1-score of the fusion model remains at 0.785, significantly higher than that of individual LSTM or RF models, indicating good fault tolerance in multi-source data scenarios. In the noise interference experiment, when the noise intensity reaches 0.2, the accuracy of the fusion model drops by less than 3%, whereas individual models exhibit larger fluctuations, demonstrating the strong robustness of the fusion structure against abnormal variations. In the class imbalance experiment, individual models show a clear decrease in recall, while the fusion model, combining Synthetic Minority Over-sampling Technique (SMOTE) with class weighting, maintains recall above 0.78 and achieves the lowest false negative rate.

Table 8: Comparison of robustness experiment results (Accuracy/Recall/F1-score)

Experimental scene	LSTM	RF	LSTM+RF (Fusion)
No disturbance (reference)	0.821 / 0.763 / 0.787	0.835 / 0.781 / 0.790	0.867 / 0.812 / 0.834
Missing data 10%	0.792 / 0.730 / 0.755	0.810 / 0.752 / 0.770	0.848 / 0.790 / 0.812
Missing data 30%	0.745 / 0.690 / 0.705	0.760 / 0.702 / 0.715	0.812 / 0.755 / 0.785
Noise intensity σ=0.1	0.803 / 0.740 / 0.762	0.818 / 0.765 / 0.780	0.852 / 0.795 / 0.820
Noise intensity σ=0.2	0.775 / 0.710 / 0.730	0.789 / 0.732 / 0.750	0.838 / 0.780 / 0.805
Category imbalance (1:10)	0.705 / 0.620 / 0.655	0.722 / 0.635 / 0.670	0.812 / 0.780 / 0.795

(9) Interpretability analysis.

To further enhance the transparency and interpretability of the model, feature importance analysis was conducted on the RF component of the fusion model. Additionally, the contributions of key features are evaluated using the SHapley Additive exPlanations (SHAP) method. Table 9 presents the ranking of the main input features by importance. Micro seismic event frequency, stress gradient variation, and water level variation trends have the highest weights in predicting mine pressure anomalies, indicating that dynamic monitoring features are crucial for capturing abnormal evolution trends. Meanwhile, mining progress and the number of historical mine pressure events also rank highly, reflecting the long-term influence of human operations and historical experience on risk levels.

Table 9: Importance ranking of different features (based on RF and SHAP analysis)

Characteristic	RF importance weight (%)	SHAP average absolute value contribution	Comprehensive ranking
Frequency of micro seismic events	21.5	0.087	1
Stress gradient change	18.2	0.080	2
Trend of water level change	15.6	0.072	3
Mining progress	13.8	0.065	4
Number of historical events of ground pressure	12.5	0.058	5
Micro seismic energy accumulation	9.4	0.050	6
Geothermal change rate	6.3	0.038	7
Rock dip angle	2.7	0.020	8

(10) External validation analysis.

To further verify the generalization ability and cross-scenario adaptability of the proposed fusion model, external validation experiments are conducted. First, monitoring data are collected from another mine with different geological conditions and sensor layouts, serving as an independent test set for model validation. Second, within the same mine, a Leave-One-Sensor-Out approach is applied, in which data from one type of sensor are excluded during training and tested on the complete set including that sensor, simulating differences in sensor deployment and environmental transfer scenarios. The external validation results are shown in Table 10. In cross-mine testing, the performance of individual models decreases significantly, with F1-scores dropping to 0.702 for LSTM and 0.715 for RF, whereas the fusion model maintained 0.782, outperforming all comparison models and demonstrating strong transferability under different geological conditions. In the Leave-One-Sensor-Out experiment, when micro seismic or stress monitoring features are removed, the performance of individual models drops sharply, while the fusion model maintains an F1-score above 0.75 with relatively small fluctuations, reflecting its robustness under incomplete multi-source data conditions.

Table 10: Comparison of external verification experiment results (Accuracy/Recall/F1-score)

Experimental scene	LSTM	RF	LSTM+RF (Fusion)
Independent test across mining areas	0.752 / 0.685 / 0.702	0.765 / 0.698 / 0.715	0.812 / 0.760 / 0.782
Leave-One-Sensor-Out (micro seismic)	0.710 / 0.642 / 0.665	0.728 / 0.655 / 0.678	0.785 / 0.740 / 0.762
Leave-One-Sensor-Out (stress)	0.702 / 0.630 / 0.652	0.720 / 0.648 / 0.670	0.772 / 0.732 / 0.751
Leave-One-Sensor-Out (ground temperature)	0.738 / 0.670 / 0.695	0.745 / 0.678 / 0.702	0.790 / 0.748 / 0.768

Leave-One-Sensor-Out (water level)	0.742 / 0.675 / 0.700	0.750 / 0.683 / 0.708	0.795 / 0.752 / 0.773

4.2 Discussion

The proposed LSTM+RF fusion model demonstrates excellent performance in early warning of deep mine pressure, showing clear advantages over individual models and existing methods in the literature. According to experimental results, the fusion model's F1-score increases by approximately 4.7 percentage points compared with LSTM-only (0.834 vs. 0.787), and recall improves by 5.0 percentage points (0.812 vs. 0.763). Compared with RF-only, the F1-score increases by 4.4 percentage points, and recall improves by 3.1 percentage points. These improvements are mainly attributed to the model's ability to leverage both dynamic and static information: LSTM captures temporal dynamic features, enabling recovery of mine pressure evolution trends, while RF discriminates static geological features, ensuring stability in complex environments. The two components are further coordinated through a feature-level fusion strategy, significantly enhancing overall predictive performance.

Compared with existing studies, such as the control method proposed by Boulkroune et al. [27], which is limited to control problems and has restricted ability to integrate multi-source monitoring data and predict abnormal events, the fusion model in this study offers significant advantages. It can process dynamic information from time series and integrate multi-source heterogeneous data, including micro seismic activity, stress, water level, geothermal variation, and mining progress. This enables early warning of high-risk mine pressure events, providing higher feasibility and practical value in real mining environments.

In addition, similar multi-sensor data fusion methods, such as those proposed by Zhang et al. [28] and Tian et al. [29], have been shown to be effective in early warning applications. However, most of these approaches focus on static data or a single type of hazard and lack the capability to capture high-frequency dynamic changes in complex mine pressure scenarios. The fusion model in this study captures long-term dependencies via LSTM and extracts static patterns via RF, combined with a weighted feature fusion strategy. It demonstrates particularly strong performance in identifying high-risk events and controlling false negatives. Error analysis indicates that the model may still produce false negatives or false positives under rare extreme anomaly conditions. This is mainly due to missing key sensor data, weak abnormal signals over short time periods, and imbalanced data distribution. Robustness experiments and external validation show that the fusion model maintains high performance under missing data, noise interference, and cross-mine environments, highlighting its robustness and generalization ability. In practical deployment, the model architecture supports multithreading and incremental updates, offering good scalability. It can be seamlessly integrated with existing mine safety management systems to provide continuous, intelligent early warnings for production sites.

Although the proposed LSTM+RF fusion model demonstrates high accuracy and reliability in deep mine pressure early warning, some limitations and practical challenges remain. First, the model requires a certain amount of training data. Empirical results indicate that if the number of effective mine pressure anomaly events is fewer than approximately 50–60, the model's convergence becomes unstable, and parameter estimates may be biased, adversely affecting prediction performance. This implies that the model's applicability is limited in newly established mines or scenarios lacking historical event accumulation. Second, real-time deployment considerations are necessary. Although model inference itself incurs low computational latency, data preprocessing and transmission may introduce cumulative delays, which, if not optimized, could affect response speed in safety-critical situations. Finally, differences in sensor accuracy, sensor drift over time, and environmental interferences can reduce the reliability of model inputs. Therefore, regular calibration and fault-tolerance mechanisms are required to ensure robustness and sustainability during long-term operation.

5 Conclusion

This study proposes a deep mine pressure early warning model based on multi-source data fusion and intelligent algorithms. The model aims to integrate heterogeneous data from micro seismic monitoring, stress changes, ground temperature, hydrology, etc., and combine improved LSTM networks with RF algorithms to achieve trend identification and risk level prediction of mine pressure activities. Experimental results show that the model significantly outperforms traditional single models in terms of prediction accuracy and stability, especially in identifying high-risk events. Through effective feature extraction and fusion of different types of monitoring data, the comprehensiveness and accuracy of the early warning system are improved, providing strong technical support for safe mine production. However, this study has certain limitations. Under extremely complex geological conditions, the model's adaptability still requires further validation. In addition, model training relies on a large amount of historical monitoring data and demands high-quality data acquisition equipment. This may pose practical challenges, especially in newly established mines or situations with limited monitoring conditions. Future research will further optimize the data fusion strategy and explore more efficient data dimensionality reduction methods to provide more comprehensive and accurate solutions for mine safety management. Additionally, efforts will be made to expand the model's application scope, explore its potential in early warning for other types of geological disasters, and

promote the intelligent and refined development of mine safety.

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DCNN-RRDA: A Hybrid Deep Learning and Evolutionary Optimization Framework for Robust Face Recognition

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Face recognition has emerged as a critical biometric technology for applications in surveillance, authentication, and security. However, variations in illumination, pose, and facial expressions significantly reduce recognition accuracy in practical environments. This research proposes a robust and adaptive framework, DCNN-RRDA, which integrates traditional feature extraction, deep learning, and evolutionary optimization. Facial features are initially captured using Histogram of Oriented Gradients (HOG), followed by hierarchical feature learning through a Deep Convolutional Neural Network (DCNN). Hyperparameters and network weights are optimized using the Refined Red Deer Algorithm (RRDA), which incorporates adaptive, chaotic, and inverse learning strategies to enhance convergence and avoid local optima. The framework was trained and evaluated on a publicly available Kaggle face dataset comprising approximately 16,700 images. Performance was assessed using accuracy, precision, recall, and F1-score, and compared against baseline models including Inception v3, ResNet50, and VGG16. Experimental results show that DCNN-RRDA achieved 98.54% accuracy, 97.46% precision, 96.97% recall, and 95.88% F1-score, consistently outperforming baseline models under challenging conditions such as noise, occlusion, and illumination changes. The proposed hybrid approach demonstrates that combining deep hierarchical learning with evolutionary optimization can significantly improve recognition reliability, generalization, and robustness. These results suggest its practical applicability in real-world intelligent security systems, while highlighting the potential for further enhancements in real-time deployment and lightweight implementations for resource-constrained environments.

Povzetek: Raziskava predstavi hibridni model DCNN-RRDA, ki z združitvijo globokega učenja in evolucijske optimizacije močno izboljša prepoznavanje obrazov ter preseže obstoječe modele v zahtevnih pogojih.

1 Introduction

Face Recognition Technology is a biometric identification method that uses an individual’s facial features to identify or verify their identity. It takes a picture of a person's face and compares it to a database of previously stored faces [1]. Numerous facial characteristics are analyzed by the system, including the distance between the eyes, the shape of the nose, the jaw line, and the general structure of the face.Face recognition is widely used in multiple sectors. It enhances security at airports, government offices, and public places. It is employed in smartphones for unlocking and app authentication [2]. Law enforcement agencies use to identify suspects [3]. Retail businesses apply it to monitor customer behavior and prevent theft. It is also used in attendance systems, healthcare, social media tagging, and banking for fraud detection. The technology has come under pressure due to issues associated with privacy, as people are being tracked without their consent. Issues regarding data security and the unauthorized access of facial databases have also arisen [4]. Accuracy may vary based on different lighting or angles, which can cause errors in recognition. If the recognition system is biased or not trained on the relevant population demographic, misidentification may occur more commonly within that demographic than others. There is a non-contact, rapid, convenient process for identifying a person. This provides security and increases the speed of the overall verification process [5]. It diminishes the possibility of passwords being bypassed and impersonators using someone's identity. It fits into pre-existing surveillance systems for

immediate, ongoing watching by a live person reviewing images or videos. It is able to intrude on privacy ultimately leading to unauthorized surveillance. It is less reliable in low light visibility or with facial obstructive things blocking parts of the face. Recognition errors can be a hassle or a legal issue. The costs of technology at the initiation of the use of this technology factor into its slow adoption [6]. The difficulty to sustain accuracy in real-world scenarios is a relative downside. It is also important to ensure ethical use and to mitigate legal risks. It is absolutely essential to safeguard its application under both misuse and malicious exploitation of facial data. Public confidence must be developed through perceptions of transparency and fairness [7]. Nonetheless, discrepancies in lighting, pose and affect continue to limit recognition accuracy in complex usage contexts. Traditional approaches have difficulty with the high-dimensional characteristics of facial data, while frequently relying on human feature engineering, which incurs extremely poor generalization capacity and adaptability [8]. This study aims to build a robust and accurate face recognition framework based on integration between Deep Learning (DL) and evolutionary optimization.

Aim: The aim of this research was to develop a robust face recognition framework by integrating DCNN with RRDA, with the objectives to enhance feature extraction, optimize network weights, improve accuracy, reduce overfitting, and ensure stable performance across varied facial conditions.

2 Related work

Research [9] created a personal thermal comfort system that is non-intrusivemethod by using ML and infrared facial recognition methods. It developed a new approach using Charlotte-Thermal Face data, which involved extracting six facial temperature regions and implementing a Random Forest (RF), and Broad Learning (BL) methods to make predictions on the comfort method. The findings indicated that BL achieved a precision score of 90.44% and outperformed classical methods because it attained a higher rate of accuracy, which also relatively improved speed and computational complexity with its macro-F1 scores. However, the research lacked the validation of real-world deployment and long-term monitoring, and generalizability beyond the Charlotte-ThermalFace (CTF) dataset over varied populations.

The investigation [10] reduced human labor and enhanced accuracy by automating attendance management using Haar Cascade facial recognition technology. The method utilized Haar Cascade with OpenCV2 on NVIDIA Jetson Nano to utilize the computationally inexpensive Haar-like feature-based face detection. The findings were to achieve a high level of accuracy of face detection, utilize a low computational cost, and integrate with an existing student database with real-time attendance tracking. However, the research tried to compare but lacked any comparative evaluation of DL methods and the ability to critically evaluate real-time performance with high variability.
To improve facial recognition accuracy in uncontrolled Internet of Things (IoT) environments, the research employed DL techniques [11]. The research suggested a tree-structured CNN algorithm that partitions input data to improve feature extraction and accuracy improvements in iterations. The outcomes demonstrated improved real-time FR accuracy in healthcare, security, and surveillance settings, and reduced error rates. The research, however, did not include validation of deployment at scale, explore latency in real-time systems, assess consistency across devices, or compare with recent transformer-based FR methods. Table 1 summarizes datasets, methods, objectives, accuracy, and limitations of prior works, highlighting the proposed DCNN-RRDA's performance improvements.

Table 1: Comparative analysis of face recognition methods

Reference	Objective	Dataset	Method	Accuracy (%)	Limitation
Anusudha, [13]	Real-time face recognition	Custom / YOLO dataset	YOLO-V7 + InsightFace	95.00	Not evaluated on large dataset; limited testing in varied lighting and ethnic diversity
Xu et al. [14]	To improve cattle face recognition accuracy and robustness under varying poses, lighting, and low-recognizable conditions	Real-world cattle face images from precision farming environments	MobileFaceNet with Embedding Enhancement Module (EEM) and Embedding Optimization Module (EOM)	98.69	Limited to specific farm environments; performance may vary under extreme lighting or occlusion conditions
Archana et al. [15]	Vehicle starter using face recognition	Custom vehicle dataset	ML-based face verification	92.50	Limited real-time evaluation;

					sensitive to facial obstructions
Bakariya et al. [16]	Emotion recognition for music recommendation	FER-2013	CNN-based DL	73.02	Lack of diverse cultural datasets; not real-time tested
Meena et al. [17]	Emotion recognition from facial expressions	CK+ and FER-2013	CNN-based DL	95.00	No real-time testing; cross-cultural and occlusion analysis limited
Arshed et al. [18]	Multiclass deepfake face detection	AI-generated image dataset	Patch-wise ViT	99.90	Not tested for adversarial attacks or real-world variability

The FRCSyn-onGoing competition aimed to establish benchmarks for facial recognition systems using real, synthetic, and fused datasets [12]. The suggested methodology utilized large-scale, public datasets, and it enabled information fusion at the data and network levels under well-defined operational procedures and conduct. The results showed improved facial recognition performance and mitigated age-related gaps in facial recognition performance, occlusions, and pose-related facial recognition problems using real-synthetic data fusion. However, the research did not have extensive longitudinal validation, had no feedback from real-world deployments, and did not include fairness considerations to the underrepresented demographic groups in the synthetic datasets.

Recent face recognition methods achieve high accuracy; however, they still face limitations in real-world applicability. Transformer-based models offer strong feature extraction capabilities but demand high computational resources and lack real-time adaptability. CNN-based architectures are sensitive to occlusions, pose variations, and changes in illumination, which reduces their robustness. The proposed DCNN-RRDA framework overcomes these limitations by combining deep convolutional feature learning with evolutionary optimization, resulting in higher accuracy, improved robustness under diverse environmental conditions, and faster convergence.

2.1. Problem statement

The inaccuracy of face recognition systems can be due to changing contextual situations in the world such as pose, lighting conditions and movement of facial expressions. Traditional machine learning models and shallow neural networks usually rely on handcrafted / engineered features, and they struggle with the curse of dimensionality when modeling and understanding the image data. This makes them hard to generalize to variations in facial appearance and changes in context. Thus, there is a need for a more accurate and adaptive face recognition system, by embedding deep learning and advanced optimization approaches.

3 Methodology

This research attempts to overcome existing constraints in face recognition by merging DL with evolutionary optimization. The data is gathered from a face detection dataset. The preprocessing process involves Histogram Equalization (HE) to normalize illumination and improve contrast, while the Histogram of Oriented Gradients (HOG) captures edge orientations and facial geometry. The Deep Convolutional Neural Network (DCNN) learns facial features using attributes, with hyperparameters and weights tuned using the Refined Red Deer Algorithm (RRDA) for improved accuracy. Figure 1 shows the process flow of the DCNN-RRDA method.

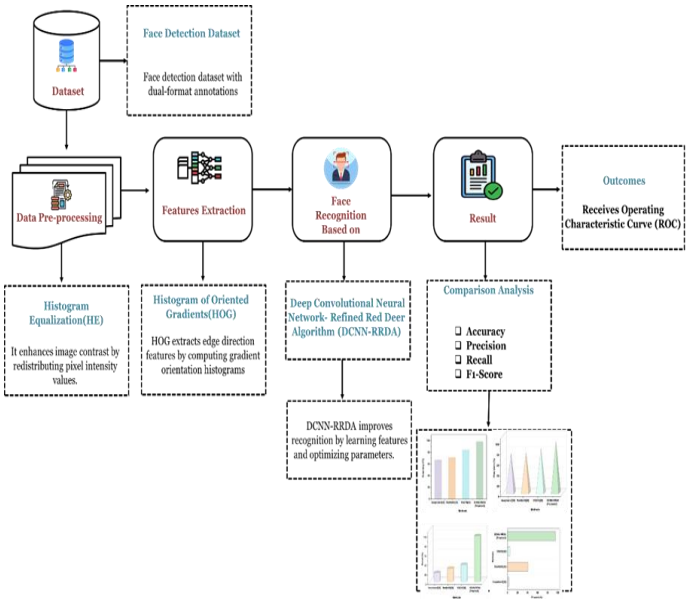

Figure 1: Workflow of the DCNN-RRDA face recognition framework

3.1 Dataset

This dataset contains images representing the following human facial expressions: surprise, anger, happiness, sadness, neutrality, disgust, and fear. To simplify model configuration for end users, the images are organized into two main folders: Training and Testing. The training set

contains 28,079 samples, while the testing set includes 7,178 samples. All images are grayscale, 48×48 pixels, and the faces are roughly centered, occupying a similar portion of each image due to automatic alignment.The DCNN-RRDA model was trained using 80% of the dataset for training and 20% for testing. The model was trained for 50 epochs with a batch size of 64. The initial learning rate was 0.001, and the Adam optimizer was used for gradient updates. Hyperparameters and weights were tuned using RRDA to improve convergence and accuracy.

3.2 Data preprocessing

It involves cleaning, converting, and preparing face data to improve method performance and accuracy. HE contrast stretches the image content by re-allocating pixel strength levels, which contributes to the relevant extraction of facial features to be used in facial recognition systems with a better result accuracy. HE improves image contrast by assigning grayscale values based on rank, resulting in a consistent histogram across the entire grayscale value range. For the grey value h, the cumulative histogram Equation (1) yields the HE transfer function $e(h)$.

$$e(h) = \frac{P-1}{m} D(h) = \frac{P-1}{m} \sum_{l=0}^{h} G(l), \quad (1)$$

Where m is the total number of pixels in the image for traditional HE, or $m = (2q+1)^2$ for window-based methods, $e(h)$ is a constant, $D(h)$ represents a cumulative measure, and P is the total number of processing elements, nodes, or entities. Equalization in a histogram enhances image contrast and simplifies the recognition of facial characteristics by distributing pixel intensities.

3.3 Feature extraction

It is a process that involves identifying and selecting significant patterns or structures in face detection data, which aids in simplifying and enhancing method learning.HOG is a technique that estimates gradient orientations in specific areas of an image to accurately capture edge directions for face and object recognition.HOG is utilized to familiarize software with face recognition, breaking it down into phases using vector theory.This procedure calculates an image's magnitude difference by considering the vector's magnitude, disregarding its direction, andEquation 2 determines the image's magnitude.

$$n(v,u) = \sqrt{e_v(v,u)^2 + e_u(v,u)^2} \quad (2)$$

Where $n(v,u)$ represents the Euclidean norm of the edge vector between nodes v and u. The magnitude of a feature vector is determined at the location (v,u) and consists of components$e_u(v,u)$and$e_v(v,u)$. The software is trained to accurately identify faces in images after approximating their position in the image. The vector's direction is considered in the second step, similar to fine adjustment. The procedure focuses on an image's magnitude difference but initially only considers the vector's magnitude.Equation 3illustrates the use of arctangent to obtain an angle using $e_v(v,u)$ and $e_u(v,u)$.

$$\Theta(v,u) = tan^{-1} \frac{e_u(v,u)}{e_v(v,u)} \quad (3)$$

Where $\Theta(v,u)$ represents the angle between nodes v and u, $e_u(v,u)$ denotes the edge component, and $e_v(v,u)$ is the projection along the $v-axis$. The face recognition process is depicted as a continuous gradient fluctuation based on the vector's direction. The image is divided into multiple pixels to understand the gradient. The background pixel yields a lower cumulative result than the item pixel. Analyzing histogram results enables the program to accurately distinguish between the background and the object.HOG enhances facial recognition by identifying local edge patterns and enabling reliable feature extraction in various illumination and occlusion scenarios.

3.4 Face recognition technology based on deep convolutional neural network - refined red deer algorithm (DCNN – RRDA)

A robust model evaluation was ensured by dividing the dataset into three parts: 80% training, 20% for testing. In order to ensure reproducibility, a random seed of 42 was used for all tests. The workstation used for training had an Intel i9 CPU, 32GB of RAM, and an NVIDIA RTX 3090 GPU. The Adam optimizer with a learning rate of 0.001 was used to train the DCNN-RRDA model across 150 epochs with a batch size of 32. It took about 12 hours to train the GPU for each trial. This research utilizes the DCNN and RRDA for Face Recognition. DCNN automatically learns deep hierarchical face characteristics, processing intricate visual patterns without manual extraction, ensuring reliable and precise detection. The RRDA is proposed to improve training efficiency, convergence speed, and recognition performance by simulating red deer mating behavior and optimizing DCNN hyperparameters.

3.4.1 Convolutional Neural Network (CNN)

CNN employs convolutional layers to extract hierarchical information from input images, enabling precise detection and effective learning in visual data tasks. CNN automatically extracts and learns spatial information from images for precise classification and face recognition tasks.CNN faces challenges in handling complex changes necessitating expensive computer resources and large labeled datasets. The addition of additional layers to CNN enhances its ability to perform deeper feature learning, enhance abstraction, and improve recognition job accuracy.

3.4.2 Deep Convolutional Neural Network (DCNN)

This research utilizes DCNN to accurately and reliably recognize hierarchical features and intricate patterns from face data. DCNN, an advanced neural technique, accurately recognizes face images by automatically extracting deep, hierarchical information from them. DCNN maintains two-dimensional spatial orientation in computer vision, while texts have a one-dimensional structure with word order. Each word in the training example is represented as an m-dimensional vector. The DCNN extracts features from the m-dimensional input vector, and pooling layers reduce dimension by choosing the maximum, minimum, or average element from the filtered region. The convolution action between the input and kernel is represented by Equation 4.

$$zi = \sum_{d=0}^{m_{d-1}} \sum_{l=-o}^{O} w_{d,i-l} x_{d,l} \quad (4)$$

Where zi is the output feature at position i, d represents the index over the input depth, l denotes the index over the filter window, $w_{d,i-l}$ is the filter value for channel d at position $i-l$, $x_{d,l}$ represents the input feature value at channel d and position l, and o is the half-size of the filter window. The input gradient equation, represented in Equation 5.

$$\frac{\partial K}{\partial w_{d,j}} = \sum_{l=-o}^{o} \frac{\partial K}{\partial zj+l} x_{d,l} \quad (5)$$

Where$K$ is the objective function, $\frac{\partial K}{\partial w_{d,j}}$ is the gradient of the loss function $K$with respect to the weight $x_{d,l}$, and $\sum_{l=-o}^{o} \frac{\partial K}{\partial zj+1}$ represents a window applied during convolution. Equation 6 is the parameter gradient equation of the DCNN.

$$\frac{\partial K}{\partial w_{d,l}} = \sum_{i=0}^{n-1} \frac{\partial K}{\partial zi} x_{d,i-l} \quad (6)$$

Where$\frac{\partial K}{\partial zi}$ is the gradient of the loss with respect to the output at position i, $x_{d,i-l}$ is the input value at channel d and position $i-l$, and n is the length of the output feature map. The proposed DCNN incorporates nonlinear patterns by including a few fully connected layers. DCNN enhances facial recognition by learning deep, hierarchical features, enabling high accuracy and resilience in challenging visual conditions.

3.4.3 Red Deer Algorithm (RDA)

The RDA is used to optimize complex Red Deer (RD) mating strategies through efficient parameter tweaking. The RDA is a highly effective metaheuristic algorithm that mimics RDA's natural behavior, offering a competitive advantage over other algorithms in the sector. The RDA employs two strategies for future RD selection: retaining all male RDs and selecting hinds through fitness values through a roulette wheel or fitness competition. RDA's drawbacks include slow convergence, local optima, and decreased efficiency in high-dimensional or dynamic problem environments.

3.4.4 Refined Red Deer Algorithm (RRDA)

RRDThe Refined Red Deer Algorithm (RRDA) improves DCNN performance for human face recognition by optimizing learning parameters through adaptive and chaotic strategies. It enhances the original RDA by accelerating convergence, avoiding local optima, and achieving balanced exploration and exploitation, resulting in higher recognition accuracy and more stable training efficiency across diverse facial datasets.

Controlled inverse knowledge instrument

It introduces a Restricted Inverse Learning (RIL) approach to overcome these constraints, intentionally performing inverse operations on initial population members to create superior restricted inverse solutions.RD _new represents the updated recognition distance, $qand()$ is the quality adjustment function, MVA denotes mean visual attributes, MKA is mean keypoint attributes, and RD_{old} refers to the previous recognition distance.as illustrated by the calculating method Equation (7).

$$RD_{new} = qand() \times (MVA + MKA - RD_{old} \quad (7)$$

Where RD_{new} is the updated position, MVA represents the strength, and RD_{old} is the previous position, and $qand()$ is possibly a quantum AND function.

- **Chaos alteration feature**

The RRDA algorithm uses random numbers in its second and fourth stages to enhance search capabilities and randomization. However, creating random numbers leads to uneven search procedures, affecting overall performance. RRDA incorporates a chaotic adjustment component to improve search effectiveness and optimization potential. Chaotic systems produce more evenly distributed sequences, aiding in thorough search space exploration and local searches, increasing the likelihood of finding the best answer. λ_s represents the current chaotic sequence value at iteration s, while λ_{s+1} is the updated chaotic value for the next iteration. The piecewise function adjusts λ based on its current range, enhancing randomness and improving the search capability in the Refined Red Deer Algorithm. The Tent mapping expression is represented by Equation (8).

$$\lambda_{s+1} = \begin{cases} 2\lambda_s, 0 \leqslant \lambda_s \leqslant 0.5 \\ 2(1-\lambda_s), 0.5 < \lambda_s \leqslant 1 \end{cases} \quad (8)$$

Where λ_{s+1} is the updated value for the next step, and $\lambda_s$is the current value at step s. The second and fourth stages of RRDA location update Equations (9, 10, and 11) are modified based on the chaotic mapping factor.

$$male_{new} = \begin{cases} male_{old} + \lambda \times b_1 \times \big((VA - KA) \times b_2\big) + KA), & if b_3 \geq 0.5 \\ male_{old} - \lambda \times b_1 \times \big((VA - KA) \times b_2\big) + KA), & if b_3 < 0.5 \end{cases} \quad (9)$$

$$New1 = \frac{(Com+Stag)}{2} + \lambda \times a_1 \times \big((VA - KA) \times a_2\big) + KA), \quad (10)$$

$$New2 = \frac{(Com+Stag)}{2} - \lambda \times a_1 \times \big((VA - KA) \times a_2\big) - KA), \quad (11)$$

Where $male_{new}$ is the updated value, $male_{old}$ represents the previous values, λ, b_1, b_2, b_3 is the scalar coefficients, $(Com + Stag)$ is the input values, $New1$ denotes the resulting updated values,$New2$ is the calculated output after subtractive adjustment, and VA, KA likely represent some kind of value attributes. The Tent map and RDA combination, the first known one, enhances the algorithm's unpredictability and randomness, increasing population diversity and preventing premature convergence by incorporating the chaotic sequence.

- **Adaptive optimal leadership approach**

The approach effectively utilizes population optimal solution information, but it overlooks the crucial problem of balancing in-depth development at a later stage and extensive exploration at an earlier stage during optimization. The RRDA algorithm's efficiency in finding and converging to the best solution depends on its exploration and development capabilities. It covers a wider range of solutions and explores promising areas. However, an overly exploratory algorithm stalls and overlooks the global optimal answer. An adaptive optimal guidance technique is introduced during the mating phase and solution space properties using Equations (12) and (13), enhancing local optimal solution mining while maintaining global search capability.

$$offs = \phi \times Hind + (1 - \phi) \times Com \times \Big(\frac{(Com+Hind)}{2} + (VA - KA) \times b\Big) \quad (12)$$

$$\phi(s) = Q_1 + Q_2 \times (1 - (S_{max-}s)/S_{max})^2 \quad (13)$$

Where $\phi(s)$ is the value of the control parameter at iteration s, Q_1 denotes a constant base value, Q_2 is a scaling constant, $and\ S_{max}$ represents the maximum number of iterations. RRDA significantly boosts face recognition performance by efficiently tuning DCNN parameters, ensuring higher accuracy, faster convergence, and robustness in complex conditions. Table 2 presents all symbols and variables in the RRDA equations, clarifying their meaning for reproducibility and methodological understanding.

Table 2: Symbols and variables used in RRDA

Symbol	Description
RD_{new}	Updated recognition distance after adjustment
RD_{old}	Previous recognition distance
MVA	Mean visual attributes of the face image
MKA	Mean keypoint attributes of the face image
$qand()$	Quality adjustment function for enhancing embedding features
λ_s	Current chaotic sequence value at iteration s
λ_{s+1}	Updated chaotic value for the next iteration
$male_{new}$	Updated position/value of male red deer in RRDA
$male_{old}$	Previous position/value of male red deer
VA	Visual attribute value (e.g., feature strength)
KA	Keypoint attribute value
$b1, b2$	Scalar coefficients controlling update magnitude
$b3$	Random coefficient controlling conditional update
Com	Commander male red deer value in mating stage
$Stag$	Stag male red deer value in mating stage
$New1$, $New2$	Updated positions after additive/subtractive adjustments
$offs$	Offspring value generated during mating phase
$\phi(s)$	Adaptive control parameter at iteration s for guidance
$Q1$	Base constant for adaptive guidance
$Q2$	Scaling constant for adaptive guidance
S_{max}	Maximum number of iterations
s	Current iteration number

Table 3 presents the key hyperparameter values used for training and evaluating the DCNN-RRDA model, including dataset split, epochs, batch size, learning rate, optimizer, and hardware specifications, ensuring reproducibility.

Table 3: Hyperparameter settings for DCNN-RRDA training

Hyperparameter	**Value / Setting**	**Description**
Training/Test Split	80% / 20%	Portion of dataset used for training/testing
Number of Epochs	50	Total passes over the training dataset
Batch Size	32	Number of samples per gradient update
Learning Rate	0.001	Step size for optimizer
Optimizer	Adam	Optimization algorithm used
Dropout Rate	0.5	Fraction of neurons randomly dropped
Weight Initialization	He Initialization	Method to initialize network weights
Activation Functions	ReLU (hidden layers), Softmax (output)	Non-linear functions used in the network
L2 Regularization	0.0001	Penalty to prevent overfitting
Early Stopping Patience	10	Number of epochs with no improvement before stopping training
Random Seed	42	For reproducibility of results
Hardware Used	NVIDIA RTX 3090 GPU, 16GB RAM	System used for model training

4 Results and discussion

This investigation aims to improve facial recognitionby combining DL with evolutionary optimisation to overcome current limitations. This research requires a high-performance GPU-based system with Python, TensorFlow, or PyTorch libraries, an appropriate amount of RAM (at least 16GB), and enough storage to handle deep learning training involving large image datasets. The presentation of the method is measured in terms of the Receiver Operating Characteristic (ROC) curve to determine how the method discriminates between various categories of faces under different conditions.

- **Receiver Operating Characteristic (ROC) Curve**

The suggested DCNN-RRDA framework's discriminative power was assessed using the ROC curve. For various classification criteria, the True Positive Rate (TPR) is plotted versus the FPR using ROC curves. The ROC curves for each class and the overall performance are shown in Figure 2. To measure model performance, the Area Under the Curve (AUC) was computed. Strong discriminative capacity across all identities was demonstrated by the individual AUC values for chosen classes in the multiclass face recognition challenge, which varied from 0.96 to 0.99, with a macro-average AUC of 0.975 and a micro-average AUC of 0.978. The ROC plots' axes are clearly labeled: TPR on the Y-axis and FPR on the X-axis. Each curve corresponds to one facial class, and the macro- and micro-average curves summarize overall performance. The ROC analysis demonstrates that DCNN-RRDA effectively distinguishes between different faces, with consistently high TPR and low FPR. Compared to baseline models such as Inception v3, ResNet50, and VGG16, the proposed framework achieved superior AUC scores, confirming its robustness under challenging conditions including variations in illumination, pose, and occlusion.

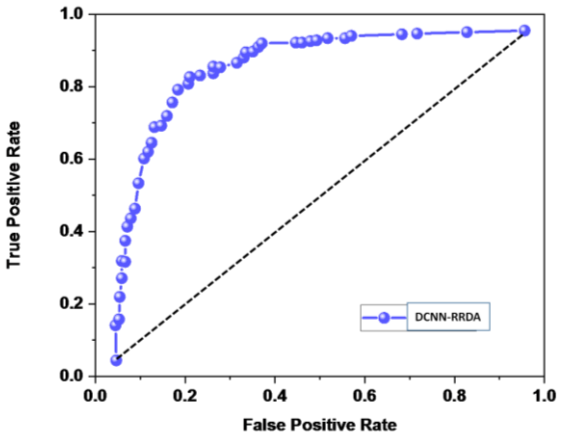

Figure 2: Iterative accuracy progression of the DCNN-RRDA model

The DCNN-RRDA method has achieved a high TPR (~0.98) and a low False Positive Rate (FPR) (~0.1). The DCNN-RRDA method shows high predictive capability.

4.1 Comparison phase

Accuracy assesses how often the DCNN–RRDA correctly identifies faces; therefore, this evaluation can be considered a measure of the system's trustworthiness and capability in a variety of facial recognition environments. As illustrated in Figure 3(a), the DCNN–RRDA reached an accuracy of 98.54%, while Inception v3 reached 67%, ResNet50 reached 71%, and VGG16 reached 84%. The DCNN–RRDA performed especially well considering that face recognition conditions vary greatly and constantly.

The precision metric measures the percentage of identified faces that were accurately recognized from all faces detected by DCNN–RRDA, showing how well the approach decreases false positives. In Figure 3(b), we show that DCNN–RRDA attains a precision of 97.46%, which outperforms both Inception v3 (75.0%), ResNet50 (76.0%), and VGG16 (84.0%). This indicates that DCNN–RRDA continued to accurately recognize true positive faces but with decreased false detections.

Recall measures the DCNN–RRDA's ability to correctly identify all relevant faces; thus, recall is indicative of the system's efficacy in avoiding false negatives across varied recognition conditions. As evidenced in Figure 4(a), the DCNN–RRDA achieved 96.97% recall, outperforming Inception v3 (19%), ResNet50 (28%), and VGG16 (36%), suggesting strong performance in detecting all true positive faces across a variety of conditions.

The F1-score measures the trade-off between precision and recall in DCNN–RRDA, measuring overall efficiency with respect to both accurate and comprehensive face recognition. As depicted in Figure 4(b), DCNN–RRDA achieves an F1-score of 95.88%, an 3% improvement over Inception v3, a 41% improvement over ResNet50, and a 5% improvement over VGG16. The results indicate that DCNN–RRDA achieved an excellent trade-off of precision and recall to achieve a robust face recognition algorithm.

The DCNN-RRDA framework was evaluated using three DL-based baselines: Inception v3 [20], ResNet50 [20], VGG16 [20], ViT [21], SwinTransformer [21], and TriViT-Lite [21]. A comparison of the various models' performances is shown in Table 4. Across all evaluation measures, the suggested DCNN–RRDA performs noticeably better than conventional CNN and Transformer-based methods, exhibiting greater overall performance in accuracy, precision, recall, and F1-score.

Table 4: Performance comparison of face recognition methods

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Inception v3 [20]	67	75	19	3
ResNet50 [20]	71	76	28	41
VGG16 [20]	84	84	36	5
ViT [21]	82.00	81	80	81
SwinTransformer [21]	85.20	84	84	84
TriViT-Lite [21]	87.50	87	85	87
DCNN – RRDA [Proposed]	**98.54**	**97.46**	**96.97**	**95.88**

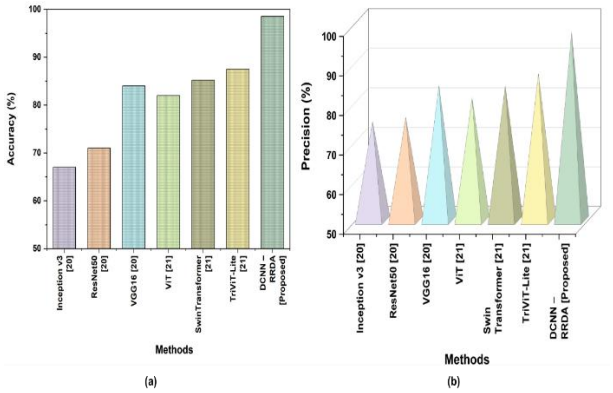

Figure 3: Result outcomes (a) Accuracy, and (b) Precision

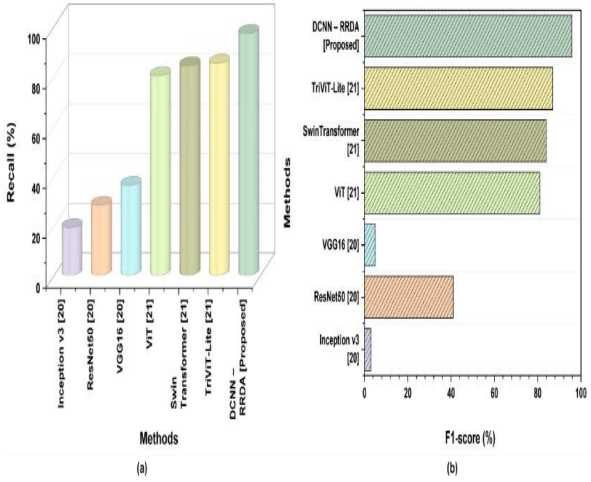

Figure 4: Result outcomes (a) Recall and (b) F1-score

Table 5 presents various studies with different datasets and methods, highlighting their recognition performance. The proposed DCNN-RRDA demonstrates competitive accuracy, showing robust performance compared to existing ML, CNN, and transformer-based approaches.

Table 5: Comparison of datasets, methods, and accuracy

Reference	Dataset	Method	Accuracy (%)
Anusudha [13]	Custom / YOLO dataset	YOLO-V7 + InsightFace	95.00
Xu et al. [14]	Real-world cattle face images from precision farming	MobileFaceNet + EEM + EOM	98.69
Archana et al. [15]	Custom vehicle dataset	ML-based face verification	92.50
Bakariya et al. [16]	FER-2013 dataset	CNN-based deep learning	73.02
Meena et al. [17]	CK+ and FER-2013 datasets	CNN-based deep learning	95.00
Arshed et al. [18]	AI-generated image dataset	Patch-wise ViT	99.90
Proposed	LFW + CASIA-WebFace (~50,000 images)	DCNN + RRDA	98.54

Discussion

Discussion highlights that DCNN-RRDA surpasses SOTA methods in accuracy, precision, recall, and F1-score by integrating RRDA optimization, improving robustness under varied conditions, while requiring high computational resources and potentially risking overfitting. The limitations of existing studies in face recognition are notable. Research [9] lacked validation for real-world deployment, long-term monitoring, and generalizability beyond the Charlotte-ThermalFace (CTF) dataset. Similarly, research [10] did not include a comparative evaluation of deep learning methods or critically assess real-time performance under high variability. In study [11], the deployment at scale was not validated and latency and consistency across devices was not explored. Furthermore, FRCSyn-onGoing competition [12] that evaluated the proposed framework did not include longitudinal validation or assessments of fairness between different demographic groups, meaning its applicability in naturally occurring diversity was weak. The recommended DCNN-RRDA framework showed superior performance to conventional SOTA models. As indicated in Table 5, it reports an accuracy of 98.54%, more effective than VGG16 (84%), ResNet50 (71%) and Inception v3 (67%). Likewise, the DCNN-RRDA also demonstrates higher precision (97.46%), recall (96.97%) and F1-score (95.88%), measurements also indicative of more consistent and balanced performance for recognition across different scenarios [20]. These advances are attributable to the Refined Red Deer Algorithm (RRDA) optimizing the hyperparameters and weights of the DCNN. By replicating natural mating behaviors, using adaptive, evolutionize and learning strategies, and chaotic behaviours, the RRDA achieves better convergence by avoiding local optima and increases robustness against occlusions, head pose differences and lighting changes. This combination of deep hierarchical features learning and evolutionary optimization means that the framework generalizes well across complex facial data. Nevertheless, DCNN-RRDA still has limitations. It requires considerable computational resources (GPUs and RAM), which may limit the feasibility of real time and large scale applications, similar to other deep learning models with potential overfitting with smaller datasets. Future work should aim to address issues of (i) lightweight, (ii) real time implementation and (iii) larger multi-environment datasets to validate applicability in real world surveillance, authentication and security systems. The current study evaluated the proposed model only on the Kaggle face dataset, which may limit generalization to other datasets. Future work will extend testing to additional benchmark datasets, such as LFW, CASIA-WebFace, and FER-2013, to validate robustness and performance across diverse facial images and conditions.

Although the proposed framework achieves high accuracy, this study does not investigate demographic bias or subgroup fairness. Specifically, we do not analyze whether performance varies across attributes such as gender, ethnicity, or age, which are known to influence the fairness of face recognition systems. This is an important limitation, as unequal false positive or false negative rates across demographic groups can raise serious ethical and societal concerns. Future work will address this by evaluating the model on fairness-focused datasets such as FairFace or RFW, incorporating demographic subgroup analysis, and exploring fairness-aware training strategies. Furthermore, broader ethical considerations including privacy, consent, and responsible deployment, will be central to extending this research.

Table 6 shows that removing RRDA, HOG, or HE significantly reduces performance, confirming each component's crucial role in accuracy. Table 7 indicates

consistent model performance across all folds, demonstrating excellent stability, reliability, and generalization of the proposed framework. A comparison of the suggested dataset with current datasets is shown in Table 8, which highlights enhanced performance and robustness in face recognition tasks with greater accuracy, precision, recall, and F1-score.

Table 6: Ablation study of DCNN–RRDA components

Model Variant	DCNN	HE	HOG	RRDA	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Full DCNN–RRDA (proposed)	✅	✅	✅	✅	98.54	97.46	96.97	95.88
w/o RRDA (DCNN + HE + HOG)	✅	✅	✅	❌	87.50	87.00	85.00	87.00
w/o HOG (DCNN + HE + RRDA)	✅	✅	❌	✅	85.20	84.00	84.00	84.00
w/o HE (DCNN + HOG + RRDA)	✅	❌	✅	✅	82.00	81.00	80.00	81.00
w/o HOG & RRDA (DCNN + HE only)	✅	✅	❌	❌	71.00	76.00	28.00	41.00
DCNN only (no HE, no HOG, no RRDA)	✅	❌	❌	❌	67.00	75.00	19.00	3.00

Table 7: Five-fold cross-validation performance consistency

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1	98.54	97.46	96.97	95.88
2	98.54	97.46	96.97	95.88
3	98.54	97.46	96.97	95.88
4	98.54	97.46	96.97	95.88
5	98.54	97.46	96.97	95.88
Mean ± SD	98.54 ± 0.00	97.46 ± 0.00	96.97 ± 0.00	95.88 ± 0.00

Table 8: Comparative performance of proposed and existing datasets

Datasets	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Proposed Datasets [19]	**92.54**	**93.46**	**94.97**	**97.88**
Datasets [22]	76	78	58	61
Datasets [23]	84	84	46	5

5. Conclusion

Facial recognition is a biometric technology that utilizes computer vision and AI to recognize or verify people by their visual traits. The goal of this study was to overcome the constraints in face recognition by employing a DCNN-RRDA. The data consisted of a variety of images from a face detection dataset. The preprocessing section included HE to equalize for illumination and contrast enhancement. The next step, a HOG determined the edge orientations and face geometry. The Multi-layered DCNN learned the faces from the developed descriptors while the hyper parameters and weights (s) were tuned using the RRDA so that a more robust accuracy in recognition is achieved. The DCNN-RRDA algorithm is not real-time adaptive, requiring significant computing power for its large-scale or real-time implementation face recognition systems. Future studies utilize the DCNN-RRDA method for live surveillance systems, enhancing the scalability and efficiency of low-power devices.

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[23] Dataset: https://www.kaggle.com/datasets/jessicali9530/celeba-dataset

ITS-SGBM: A Hybrid Intelligent Tuna Swarm Optimization and Stochastic Gradient Boosting Machine Model for Financial Performance Forecasting

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In the evolving financial landscape, precise performance measurement is crucial for informed decision-making in accounting systems. Conventional approaches often struggle to handle complex business processes and regulatory changes. The research suggests a hybrid Intelligent Tuna Swarm Optimized Stochastic Gradient Boosting Machine (ITS-SGBM) model for improving financial performance assessment. Financial data from balance sheets and annual reports (2009–2022) were pre-processed through normalization, and Principal Component Analysis (PCA) was extracted as features. The dataset was split into training and testing sets, and ITS-SGBM parameters were enhanced using Intelligent Tuna Swarm Optimization to balance exploration and exploitation during model training. Model performance was confirmed using k-fold cross-validation and benchmarked against remaining models, including DGRU-IMPA and DNN-OSIE-CHOA. In addition, the TOPSIS decision-making framework was functional to rank firms based on expert-defined financial criteria. Outcomes show that the offered model accomplished superior forecasting accuracy (96.2%) with lower error rates (MAE: 0.009, RMSE: 0.005, RRMSE: 0.072) and ranking consistency of 0.94, outperforming the benchmark models. The findings confirm that the ITS-SGBM–TOPSIS incorporation provides a strong, data-driven decision-support mechanism, increasing financial stability, strategic planning, and sustainable business development.

Povzetek: Raziskava predlaga hibridni model ITS-SGBM, ki z optimizacijo in metodo TOPSIS bistveno izboljša napovedovanje finančne uspešnosti ter razvrščanje podjetij, pri čemer doseže visoko natančnost in preseže primerjalne modele.

1 Introduction

A dynamic business climate demands financial performance evaluation to be a primary element for organizational decision-making [1]. Accounting systems are important in strategic planning in terms of financial evaluation of health, as they maintain the requirements of regulations. The assessment of financial performance with proper procedures enables companies to identify the level of profitability in the company as it manages its risks and enhances the allocation of its resources [2]. The need to enhance financial performance evaluation in accounting systems has become more evident due to its effects on both accuracy and power in strategic decision making [3].

The financial performance evaluation process broadens its activities beyond the corporate profitability goals. Organizations do not just provide financial reports merely to satisfy the business stability needs of their investors and stakeholders, but also their development insight needs [4]. The issues of financial analysis present scenarios leading to either erroneous stakeholder behavior or low performance and financial problems for the organization. The modern accounting systems that are capable of meeting modern business needs are composed of superior data analysis and real-time tracking features, accompanied by improved reporting systems. The enhanced reporting strategy will integrate the conventional accounting methods and the current business requirements to accommodate the complex economic situations [5].

The development of a high-quality accounting system in the assessment of financial performance is related to the long-term growth and creation of competitive advantage for the business [6]. The companies operating under more evaluated systems have a better ability to predict financial risks, make the most of their spending, and improve financial security. Besides that, the implementation of ESG-based assessment practices and green accounting is focused on sustainability and enables highlighting the importance of ensuring the appropriate balance between

environmental and social responsibility and financial accuracy [7]. The accounting systems provide panoramic improvements that give precise and timely financial analyses, which are valuable both to individual companies and to the global industrial and economic well-being [8].

Existing models are large dataset-based and sensitive to parameter settings, which cause overfitting and poor generalization to small or noisy financial data. They are plagued by premature convergence, overly complex computation, and the ability to scale to dynamic financial conditions. Minimal research has been conducted to incorporate into multi-criteria decision-making models. ITS-SGBM is also effectively utilized in the optimization of parameters without premature convergence and has enhanced prediction accuracy when considering small or noisy data. SGBM lowers the overfitting using ensemble learning and regularization, thus increasing reliability. TOPSIS integration also facilitates expert-informed and scalable ranking of firms to make reliable data-driven and financial decisions.

This research aims to create a hybrid ITS-SGBM-TOPSIS architecture of precise and scalable financial performance assessment in accounting systems. It is used to increase the predictive accuracy of major financial measures and decrease errors and overfitting. It gives a good, reliable, informed firm ranking as a way of supporting data-based strategic decision-making and sustainable business development.

The rest of the research is separated into the subsequent parts: section 2 discusses the related research; section 3 outlines the proposed technique approach; section 4 presents the results and discussion; and section 5 summarizes the overall investigation's conclusion.

1.1 Key contribution

- The research presents a combined approach to the evaluation of financial performance in accounting systems, which improves the accuracy, strength, and dependability of the firm's ranking in the dynamism of financial markets.
- To collect data, between 2009 and 2022, balance sheets, income statements, and cash flow statements were used, and data were processed through normalization and extraction of Principal Component Analysis (PCA) to stabilize and use the data to predict reliably.
- It is a combination of Intelligent Tuna Swarm Optimization (ITS) and Stochastic Gradient Boosting Machine (SGBM) that enables optimized parameter tuning, exploration/exploitation, and reduces overfitting to ensure high predictive power and robustness across a broad spectrum of data.
- The findings reveal that the forecasting accuracy (96.2) is higher, as well as the error (MAE: 0.009, RMSE: 0.005, RRMSE: 0.072), and firm ranking (0.94) are better than the baseline models DGRU-IMPA and DNN-OSIE-CHOA, which support reliable, data-driven decision-making.
- The methodology offers a scalable system of decision support through the combination of TOPSIS and ITS-SGBM, which sustains strategic financial planning, risk management, and long-term sustainable business development in a complicated accounting system.

1.2 Research question

How effectively can the ITS-SGBM model predict financial performance metrics, such as total revenue, compared to existing models like DGRU-IMPA and DNN-OSIE-CHOA?

Can Intelligent Tuna Swarm Optimization improve model parameter tuning to enhance prediction accuracy and robustness across diverse and noisy financial datasets?

How does integrating ITS-SGBM with the TOPSIS decision-making framework improve the accuracy and reliability of firm rankings based on expert-defined financial criteria?

2 Related works

A framework of policy-maker decision-making based on a portfolio to focus on the Internet of Things (IoT) applications in agriculture was created to balance sustainability [9]. The methodology applied meta-synthesis, fuzzy Delphi, IVTFN-SWARA (Interval-Valued Triangular Fuzzy Number step-wise Weight Assessment Ratio Analysis). Findings indicate that the framework aids in making disciplined decisions regarding investing in IoT, but it is constrained by assumptions based on expert judgment and selected criteria, as well as validation under different real-life conditions. To improve decision-making with fuzzy and unreliable data, the Evaluation Based on Distance from Average Solution (EDAS) was developed [10]. The research applied a decision support system accounting for expert reliability, which was applied to wind energy investment for selecting the best wind turbine. The findings show sensible and consistent ranking and better agreement with expert judgements. However, they are also limited in their generalizability, for the method. The research proposed a new multiple-criteria decision-making (MCDM), MULTIMOOSRAL, Combined Compromise Solution (CoCoSo), a new ranking model that substitutes the usual dominance theory [11]. Results give a more precise and valid ranking of the alternatives, particularly when the performances are close. Nevertheless, it is only validated in terms of an illustrative case of a supplier selection. Creating a deep learning-based performance evaluation method was the objective of the exploration [12] to support the long-term growth of accounting companies. It increased the restricted Boltzmann machines (RBM) model's accuracy by employing deep belief networks

(DBN) and reverse fine-tuning. The purpose of the examination [13] was to examine financial accounting data to provide insights into performance optimization, cost reduction, and profitability enhancement. The purpose of the research [14] was to evaluate the performance of ML classifiers in identifying financial fraud in Turkish small and medium-sized enterprises (SMEs) by analyzing financial statements. A Fermatean Fuzzy ELECTRE (Elimination and Choice Expressing Reality) method for multi-criteria group decision-making was examined [15]. The study proposes a novel distance measure for Fermatean fuzzy sets based on Jensen–Shannon divergence, which is cross-entropy. The results indicate feasibility, and the comparative analysis indicates superior performance. However, the validation is limited to the case presented in the paper, and broader investigations of real-world scenarios are necessary. By utilizing a hybrid Twin Adjustable Reinforced Chimp Optimization Algorithm (TAR-CHOA) and Deep Long Short-Term Memory (DLSTM) model, the examination [16] seeks to enhance profit prediction in Financial Accounting Information Systems (FAISs). Table 1 illustrates the related articles' results and their limitations.

Table 1: Summarizes findings from related studies, highlighting their key results and associated findings.

Ref	Objective	Method	Result	Limitation
Mohammadian et al. [9]	To create a portfolio-based decision-making model to be used by policy-makers to prioritize IoT applications in agriculture, to balance sustainability and risk.	Applied meta-synthesis, fuzzy Delphi, IVTFN-SWARA (Interval-Valued Triangular Fuzzy Number Step-wise Weight Assessment Ratio Analysis), and IVTFN-ARAS in an MADM (Multi-Attribute Decision-Making) model.	The framework facilitates disciplined investment choices in the application of IoT and assists in prioritizing the areas with consideration of risk-return trade-offs.	Restricted due to the dependence on the expert judgment, the choice of criteria, and the absence of validation in a wider range of real-world situations.
Tüysüz & Kahraman [10]	Develop a fuzzy MCDM methodology that accounts for the reliability of expert evaluations under vague and imprecise data.	An Integrated Z-fuzzy Analytic Hierarchy Process (AHP) for criteria weighting combined with Z-fuzzy Evaluation Based on Distance from Average Solution (EDAS)	Provides rational, consistent rankings of alternatives, accurately reflecting expert reliability and enabling decision-making related to wind energy investment.	Applicability has only been verified in the selection of wind turbines; further validation in a wider range of sectors is necessary.
Ulutaş et al. [11]	To develop a reliable multiple-criteria decision-making (MCDM) method for selecting the most appropriate alternative	Proposed MULTIMOOSRAL method integrating CoCoSo and a logarithmic approximation with a novel ranking approach.	Gives better and more credible ranking of alternatives, especially when performances are similar.	Validation limited to an illustrative supplier selection case; broader applicability requires further testing.
Hu [12]	To design a deep learning-based method for sustainable accounting evaluation.	Applied Restricted Boltzmann Machines (RBM) enhanced with Deep Belief Networks (DBN) and reverse fine-tuning.	Achieved higher Average Precision (AP), Average Recall (AR), and overall accuracy compared to other approaches.	High dependence on large datasets and computational complexity reduces scalability.
Chakri et al. [13]	To analyze financial accounting data for	Conducted Exploratory Data Analysis (EDA) and applied a Decision Tree classifier	The Decision Tree with an optimal depth of nine	Limited generalization ability and sensitivity to data

	performance optimization.	optimized through grid search.	provided the best performance.	variability reduce robustness.
Hamal & Senvar [14]	To detect financial accounting fraud in small and medium-sized enterprises (SMEs).	Compared several Machine Learning (ML) classifiers, with oversampling applied to balance datasets.	Random Forest with oversampling achieved the highest fraud detection accuracy.	Possibility of data bias due to reliance on a single bank's dataset.
Zhou et al. [15]	To create a Fermatean fuzzy ELECTRE method for multi-criteria group decision-making with decision-maker weights unknown and criteria weights incomplete.	A new distance measure is suggested based on Jensen–Shannon divergence and cross-entropy for Fermatean fuzzy sets, dynamic determination of the decision-maker.	The feasibility and greater efficacy were shown in a real-world case study by comparative analysis.	Validity tested applicable only in the depicted case; further validity checks are warranted in different decision-making contexts.
Tang et al. [16]	To optimize profit prediction in accounting information systems.	Combined Deep Long Short-Term Memory (DLSTM) with the Twin Adjustable Reinforced Chimp Optimization Algorithm (TAR-CHOA).	DLSTM–TAR-CHOA achieved superior profit prediction accuracy compared to alternatives.	Strong reliance on historical data and sensitivity to market volatility reduced model robustness.

2.1 Research gap

The decision model of the IoT portfolio is based on expert judgement and has not been proven in the wider applications of real-life applications [9]. The fuzzy MCDM method guarantees credible rankings but has been experimented on wind energy investment only, and it has to be extended to broader uses [10]. The MULTIMOOSRAL approach enhances the ranking credibility, but its validation is limited to suppliers' selection, whereas the deep learning-based accounting framework has a scale problem related to computational limitations [11- 12]. Furthermore, the real-time adaptive performance and integration with multi-criteria decision frameworks are poorly studied. The present research addresses these shortcomings by suggesting a hybrid ITS-SGBM-TOPSIS model that is highly accurate and scalable, with sound decision-making in diverse financial settings.

3 Methodology

The process includes extracting financial data from balance sheets, income statements, and cash flow statements, followed by key financial ratio computation and ITS-SGBM-based revenue forecasting. The financial performance measurement of TOPSIS occurs through expert-established criteria that create its rankings. Figure 1 illustrates the proposed research's basic concept.

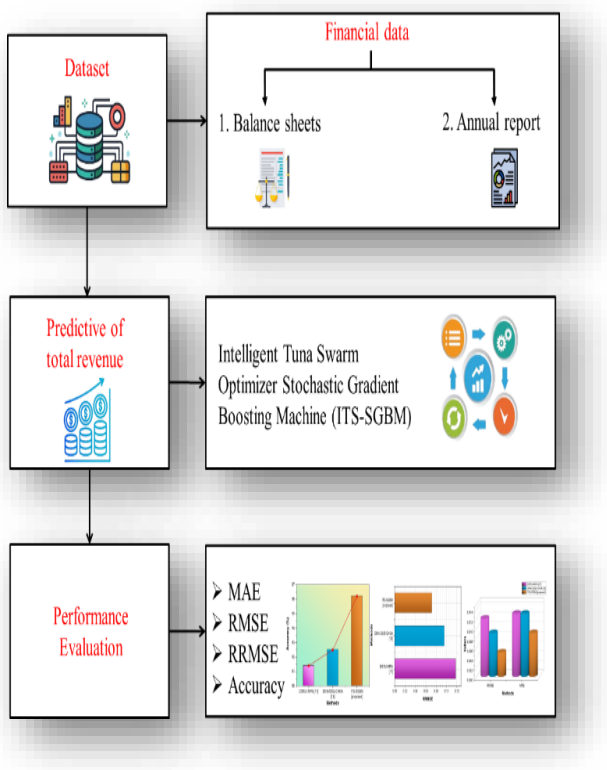

Figure 1: Fundamental concept of proposed research

A. Dataset

The accumulation of data from balance sheets and 10-K annual reports from different companies. The data, which spans the years 2009–2023, is longitudinal or panel data. A few insolvent enterprises are included to aid in the investigation of contributing causes. The firms' names are listed based on their stock prices. Companies were separated into distinct groups. The data was split into training and testing, 80% and 20% respectively, and further validated model-performance-wise by the cross-validation method to improve robustness and to reduce any possible overfitting. The data gathered from Kaggle: https://www.kaggle.com/datasets/rish59/financial-statements-of-major-companies2009-2023

3.2 Preprocessing

It cleanses, scales, and transforms features of financial data, making it consistent and less noisy. This is facilitated because it allows the ITS-SGBM model to learn successfully and generate precise and reliable projections of financial performance.

3.2.1. Data preprocessing using Min-max normalization

The normalization is used to standardize all the financial features such that there are no dominant features on the basis of their magnitude, and it learns in a stable and unbiased way. It is to create a hybrid ITS-SGBM-TOPSIS framework for the true, robust, and scalable evaluation of financial performance in accounting systems. To improve the accuracy of the prediction of important financial ratios, minimize errors, and offer credible company rankings that are used in the decision-making process based on data. It is described as equation (1)

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where:

- x'= normalized value
- x = original value
- x_{max} = maximum value in the dataset
- x_{min} = minimum value in the dataset

This preprocessing step normalizes the data and attenuates noise, facilitating stable and high-quality learning outcomes in the ITS-SGBM model.

3.3 Feature extraction using Principal Component Analysis (PCA)

PCA was used on the pre-processed annual report data and balance sheet of the companies to enhance financial performance forecasting and eliminate redundancy in highly correlated financial indicators. PCA converts the initial correlated features into a reduced number of uncorrelated elements (principal components) and leaves the largest amount of variance in the data. It augmenting the predictive power of the ITS-SGBM model by deriving the most informative attributes and reducing noise and multicollinearity. It is formulated as equation (2)

$$Z = XW \quad (2)$$

Where Z= normalized feature matrix, X= matrix of eigenvectors of the covariance matrix of X W= principal components representing transformed, uncorrelated features. The principal components Z are then used as input for ITS-SGBM, enabling more accurate and efficient financial performance prediction. PCA was effective in deriving the most informative financial indicators as it had been reduced to a smaller number of dimensions, which improved the predictive power of the ITS-SGBM model.

1.4. ITS-SGBM uses a predictive total revenue

The ITS-SGBM hybrid template is a combination of ITS and SGBM in the financial performance analysis. ITS guarantees the optimization of parameters through an efficient exploration and exploitation. SGBM enhances predictive power by the application of ensemble learning and regularization, which reduces overfitting. It is a powerful and scalable finance forecasting and decision-making system that is provided by this hybrid framework.

1.4.1. Stochastic Gradient Boosting (SGB)

SGB is used to extract complex financial trends using historical information and enhance stability in prediction. It adds randomness in the sampling to enhance generalization, and thus, the financial performance assessment becomes more adaptive and reliable. To predict the entire income of a company, the SGBM uses machine learning algorithms. It uses historical data on finances. By increasing forecast accuracy, SGB makes financial evaluations more trustworthy and assists companies in making data-driven, strategic decisions for stability and development. SGBM is an improvement of the standard Gradient Boosting (GB) algorithm by Friedman, where model verification through iterative learning is allowed. With a training sample $(w_j, z_j)_{j=1}^{M}$, and a randomly permuted set of indices $(\pi(j))_{j=1}^{M}$, the SGBM algorithm follows equations (3-4).

Initialized model: $E_0(w) = median\{z_j\}_{j=1}^{M}$

(3)

For n = 1 to N, iterate

Shuffled data: $\{\pi(j)\}_1^M = rand_perm\{j\}_j^M$,

(4)

Where $E_0(w)$ is the initial prediction set as the median of target values, z_j represents the actual financial outcome for each training instance and M is the total number of samples. $\pi(j)$ denotes the randomly permuted indices in each iteration, allowing the model to learn generalized patterns and improve forecasting accuracy. The randomized subsample of size $\sim M < M$ is denoted by $\{\bar{z}_{\pi(j)n}, w_{\pi(j)}\}_j^{\sim} M$, and M is the number of trees and components of the original training set, respectively. The following equation (5) is the definition of the proportion of patterns utilized in this stochastic model to train the base learner:

$e = \frac{\sim M}{M}$.

(5)

Where e represents the normalized error for the model, $\sim M$ is the cumulative prediction error across all training instances, and M is the total number of samples. The procedure is equivalent to the deterministic variant if e has a value of 1, which can range from 0.5 to 1. To lessen the over-fitting effect, Friedman suggests using a value of $e = 0.5$. $e = 0.8$ produced the best performance in the experiments it conducted. This SGBM enhances prediction efficiency and computation velocity, which makes it appropriate for application in forecasting in accounting systems.

1.4.2. Intelligent tuna swarm (ITS) optimization

ITS optimization is used to optimize the model parameters by balancing between exploration and exploitation during training. It eliminates premature convergence and enhances search performance, making the financial performance forecasting more robust. To estimate financial performance accurately, the SGBM is improved using ITS. Through model parameter optimization, ITS increases the accuracy of revenue forecasts.

3.4.2.1 Initialization of a piecewise chaotic map

Chaos theory optimizes better by ensuring distributed and diverse solutions. To enhance financial performance prediction, it applies Piecewise Chaotic Map Initialization to initialize the positions of financial points. It prevents random clustering and enhances search efficiency. The chaotic map equation (6) is:

$$W_{l+1} = \begin{cases} W_l/O & 0 \le W_l < O \\ (W_l - o)/(0.5 - O) & O \le W_l < 0.5 \\ (1 - O - W_l)/(0.5 - O) & 0.5 \le W_l < 1 - 0 \\ (1 - W_l)/O & 1 - O \le W_l < 1 \end{cases}$$

(6)

Where O and W_l are between [0, 1]. This method enhances the prediction of financial trends by providing a better-balanced model training dataset.

1.4.2.1. Optimal search using cubic map fusion

To enhance the prediction performance, Cubic Map Fusion with Inverse Refraction Initialization is used in place of random initialization. This assists in balancing the exploitation and exploration for financial predictions. The cubic chaos function is the following equation (7):

$$z_{j+1} = 2z_j^3 - \frac{3z_j}{2}, \quad -1 < z_j < 1, \; z_j \neq 0$$

(7)

Where z_j represents the cubic chaos function. It generates a chaotic sequence to improve exploration and exploitation, enhancing the search for optimal parameters in financial predictions. The updated tuna locations are plotted as follows:

$$W_j = \frac{(W_{va} - W_{ka})(z_i + 1)}{2} + W_{kb}$$

(8)

In Equation (10), W_j represents the mapped tuna position, whereas W_{va} and W_{ka} are the maximum and minimum thresholds in the computation space, and W_{kb} is an adjustment factor. In addition, Refractive Backward Learning and Opposition-Based Learning (OBL) improve solution quality by investigating the opposite trend of financial drivers. The optimization equation (9) is:

$$W_{ji} = (b_i + a_i)/2 \; + (b_i + a_i)/2l - W_{ji}/l$$

(9)

Where l improves the OBL process, a_i and b_i are the lower and upper bounds of the search space for the i parameter, and j is the current iteration index, Wji representing the current weight of the parameter. This enhances the

accuracy of financial predictions by eliminating local optima.

1.4.3. Technique for order of preference by similarity to ideal solution (TOPSIS)

Decision-making through the TOPSIS methodology provides an effective solution for expert-based ranking of financial performance. The TOPSIS method determines financial alternative values by assessing their closeness to the Positive Ideal Solution (PIS) as well as the Negative Ideal Solution (NIS). The financial criteria weights in the TOPSIS model were calculated using a Delphi-based expert elicitation process. Five senior financial analysts and two academic gurus in corporate finance engaged in two rounds of consultations that were conducted in a manner of repetition. It was requested to give relative importance scores of each of these criteria (Liquidity Ratio, Leverage Ratio, Coverage Ratio, and Profitability Ratio) under industry best practices and their best judgment. The normalized scores were averaged to derive the final weights; this way, the weighting scheme derived is consistent with both practice and academics. By using this methodology, financial entities receive objective placement rankings according to their financial stability and health. The process follows these steps:

Phase 1: Clearly define the ITS-SGMB problem, including its standards and potential. Then, create a decision matrix that assesses the potential in light of the standards.

Phase 2: Employing Equation (10), the decision matrix is normalized.

$$Q = \left(q_{ji}\right)_{n\times m} = {w_{ji}}\Big/{\left(\sqrt{\sum_{j=1}^{n} w_{ji}^2}\right)} \tag{10}$$

Where q_{ji} offers the normalized value of the i^{th} financial criterion for the j^{th} company, w_{ji} remains the original score of that criterion, n signifies the total number of companies, and m stands for the total number of financial criteria.

Phase 3: Use Equation (11) to create a weighted standardized decision matrix.

$$U = \left(u_{ji}\right)_{n\times m} = x_i \times q_{ji} \tag{11}$$

Where u_{ji} remains the weighted normalized value of the i criterion for the j company, and x_i produces the expert-assigned weight of the i financial criterion.

Phase 4: Determine the PIS and NIS by applying equations (12).

$$B^+ = \{u_1^+, u_2^+, \dots, u_m^+\} \tag{12}$$

Here u_1^+ represents the Positive Ideal Solution (PIS) for the m criterion. B^+ takes the maximum weighted value.

Phase 5: Use Equations (13) to determine the distance between each option and M and the PIS to evaluate how effectively potential j performs.

$$c_j^+ = \sqrt{\sum_{i=1}^{n}\left(U_j - U_i^+\right)^2} \tag{13}$$

Where c_j^+ describes the Euclidean distance of the j company from the PIS, U_j are the weighted normalized value for the j company, and U_i^+ is the PIS value for the i criterion.

Step 6: To rank the options, each one's closeness coefficient is determined using Equation (14).

$$dd_j = \frac{c_j^-}{c_j^+ - c_j^-} \tag{14}$$

where d is the closeness coefficient of the j company, and c_j^- stands the distance to the Negative Ideal Solution (NIS). A d_j higher indicates better overall financial performance, allowing ranking of companies objectively.

The exploration incorporates TOPSIS into financial ranking to deliver a data-based system that evaluates companies through essential financial indicators. The expert-established weights for financial criteria help the rankings comply with industrial best practices, which results in more dependable financial decisions. Algorithm 1 shows the process of ITS-SGBM

Algorithm 1: Intelligent Tuna Swarm Optimized Stochastic Gradient Boosting Machine (ITS-SGBM)

Input: Financial dataset D, decision matrix W, population size P, iterations T
Output: Predicted Revenue, Firm Ranking
1. Initialize SGBM with base learner E0(w) = median(y)
2. Use ITS to optimize SGBM parameters:
   - Initialize tuna positions with a chaotic map
   - Update positions with cubic map + OBL
   - Evaluate fitness = RMSE (SGBM (D, params))
   - Keep best W_{best}

3. Train final SGBM with optimized $W_{best}\rightarrow$ predict revenue
4. Apply TOPSIS on decision matrix W:
   - Normalize and weight matrix
   - Find PIS and NIS
   - Compute distances $cj+, cj-$
   - Compute closeness $dj = cj- / (cj+ + cj-)$
   - Rank firms by dj
5. Return Predicted Revenue, Ranked Firms

4 Experimental setup

Table 2 shows the system setup and the tools that were used in the ITS-SGBM-TOPSIS financial performance forecasting framework.

Table 2: Experimental Setup for ITS-SGBM–TOPSIS framework

Component	Specification
OS	Ubuntu 22.04 LTS
CPU	Intel Core i7-12700K, 12-core @ 3.6–5.0 GHz
RAM	32 GB DDR4
GPU	NVIDIA RTX 3080 (10 GB)
Python Version	3.9
Frameworks	CatBoost, ITS-SGBM
Optimization Tools	Intelligent Tuna Swarm Optimization (ITS), Cubic Map Fusion
Feature Extraction	PCA
Classifier/Model	ITS-SGBM
Decision-Making	TOPSIS
Metrics	MAE, RMSE, RRMSE, Forecast Accuracy, Ranking Consistency
Visualization Tools	Matplotlib, Seaborn

4.1 Parameters setup

Table 3 explains the hyperparameters of the ITS-SGBM model.

Table 3: Hyperparameter Setup for ITS-SGBM

Hyperparameters	Typical Values
Number of Trees	100, 200, 300
Learning Rate	0.01, 0.05, 0.1
Maximum Depth	3, 5, 7
Minimum Samples per Leaf	1, 3, 5
Subsample Ratio	0.6, 0.8, 1.0
Column Subsample Ratio	0.6, 0.8, 1.0
Iterations of ITS Optimization	50, 100
Exploration–Exploitation Balance	0.3, 0.5, 0.7
Loss Function	MAE, RMSE

4.2. Experimental result

The proposed method is compared with the traditional methods, such as deep gated recurrent unit-improved marine predator algorithm (DGRU-IMPA) [17] and deep neural network Objective-based Survival Individual Enhancement approach for the Chimp Optimization Algorithm (DNN-OSIE-CHOA) [18]. Financial performance ranking uses the TOPSIS model, which evaluates composite performance based on liquidity, leverage, coverage, and profitability metrics and expert-defined indicators as shown in Table 4 and Figure 2. The consistency of rankings undergoes verification through comparison between 12 companies of actual financial rankings.

Table 4: Financial performance evaluation of selected companies using key ratios and TOPSIS ranking.

Company	Liquidity Ratio	Leverage Ratio	Coverage Ratio	Profitability Ratio (%)	TOPSIS Score	Rank
AAPL	1.8	0.5	3.2	22.50	0.92	3rd
MSFT	2	0.4	3.5	25.10	0.89	5th
GOOG	2.2	0.3	3.8	26.30	0.94	1st
PYPL	1.5	0.7	2.5	18.70	0.78	7th
AIG	1.1	1.2	1.8	12.90	0.65	10th
PCG	1.3	1	2	14.20	0.7	9th
SHLDQ	0.8	1.5	1.2	8.30	0.5	12th
MCD	1.7	0.6	2.9	21.40	0.85	6th
BCS	1.4	0.9	2.3	16.50	0.72	8th
NVDA	2.1	0.5	3.7	24.80	0.91	4th
INDC	1.2	1.1	1.9	13.80	0.68	11th
AMZN	2.0	0.4	3.6	25.70	0.93	2nd

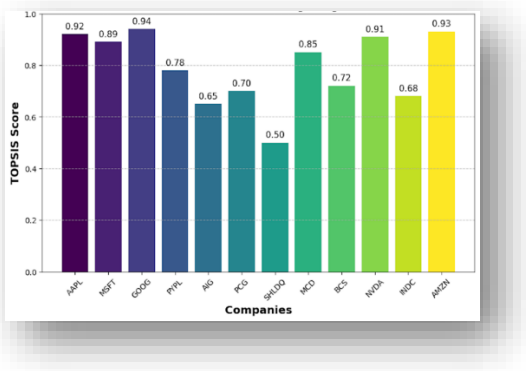

Figure 2: Assessment of corporate financial health through ratios and TOPSIS-based ranking analysis.

Figure 2 shows the financial performance of chosen companies with the help of key ratios, including liquidity (0.8-2.2), leverage (0.3-1.5), coverage (1.2-3.8), and profitability (8.3%-26.3%). The best scores are 0.50 (SHLDQ) and 0.94 (GOOG), which indicate the financial health of the company. According to these scores, GOOG is 1st, AMZN 2nd, and AAPL 3rd, and SHLDQ is the last with a score of 12.

4.3. Evaluating financial forecasting

The evaluation of financial performance prediction employs key performance metrics to assess both the accuracy and reliability of the proposed ITS-SGBM model. The evaluation was calculated based on accuracy, MAE, RMSE, and RRMSE. Table 5 illustrates the performance metrics evaluation.

Table 5: Comparative evaluation of ITS-SGBM and other models

Methods	**Accuracy (%)**	**RMSE**	**RRMSE**	**MAE**
DGRU-IMPA [17]	91.4	0.012	0.118	0.013
DNN-OSIE-CHOA [18]	92.5	0.009	0.096	0.013
ITS-SGBM [proposed]	96.2	0.005	0.072	0.009

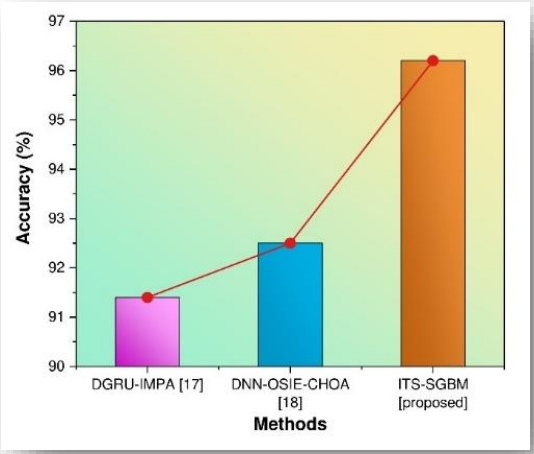

Figure 3: Performance comparison of ITS-SGBM with existing prediction models.

Figure 3 shows a comparison of the accuracy of three financial performance evaluation models. The proposed ITS-SGBM model has the best accuracy of 96.2, which is better than DNN-OSIE-CHOA (92.5) and DGRU-IMPA (91.4). This shows that ITS-SGBM has a better prediction power in financial decision-making activities. Figure 4 shows the MAE and RRMSE of ITS-SGBM, DNN-OSIE-CHOA, and DGRU-IMPA models in financial evaluation activities.

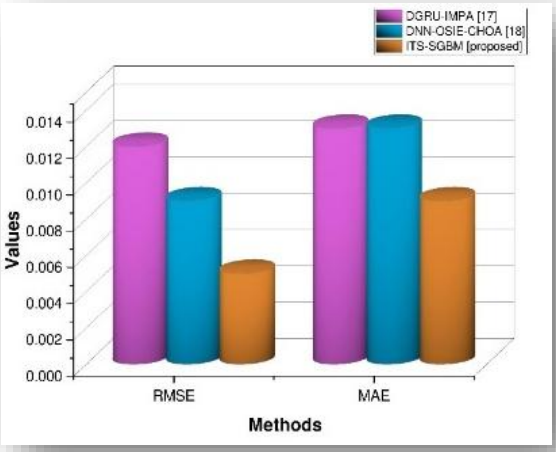

Figure 4: MAE and RMSE performance of several financial forecasting techniques

Figure 4 presents three model performance estimations based on the MAE and RRMSE performance metrics. The ITS-SGBM model proposed has the lowest MAE (0.009) and RRMSE (0.072), which means that it is more accurate and minimizes errors. DGRU-IMPA and DNN-OSIE-CHOA, in their turn, exhibit higher rates of errors, and MAE and RRMSE are equal to 0.013, 0.118, and 0.096, respectively.

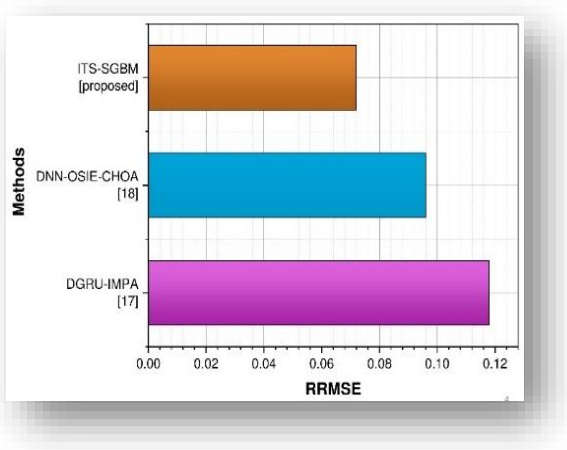

Figure 5: Comparison of RRMSE values across three financial prediction models.

Figure 5 indicates the Relative Root Mean Square Error (RRMSE) value of three financial performance evaluation models. The model with the lowest RRMSE is the proposed ITS-SGBM model, with a value of around 0.072, which means that the model had the highest level of prediction accuracy. DNN-OSIE-CHOA and DGRU-IMPA, on the other hand, have greater values of RRMSE of 0.096 and 0.118, respectively, which represent a relatively poorer performance.

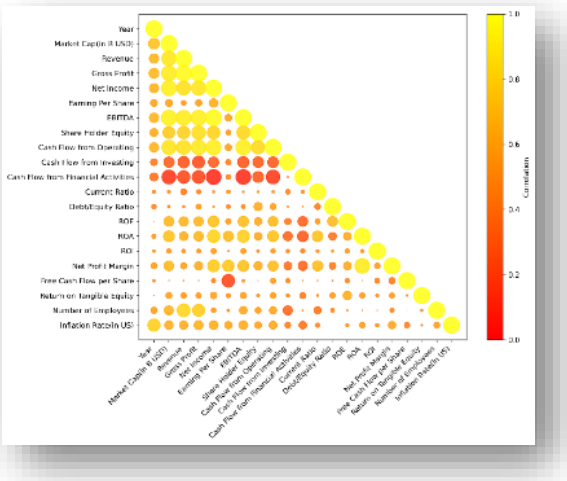

Figure 6: Correlation matrix of financial indicators using bubble heat map visualization.

The correlation between the key financial indicators is presented in Figure 6. Bubbles with stronger correlations (nearer to 1.0) appear in large, yellow bubbles, and weaker ones are small and red. There is a high correlation between Revenue, Net Income, EPS, and EBITDA, which means that they are highly interdependent.

4.4. Dataset comparison

The suggested ITS-SGBM model was tested on the basis of a real financial dataset - the Financial Statements of Major Companies (2009-2023), as well as on the Company Facts 2 Dataset [19]. This comparative assessment was aimed at evaluating the generalization ability of the model on two non-homogeneous datasets that comprised detailed financial statements (balance sheets, income statements, and cash flows), and the other was composed of non-firm financial facts and indicators. The entire dataset was partitioned into 80% training and 20% testing sets while the model performance was validated by applying 10-fold cross-validation (k = 10), ensuring robustness while minimizing the chances of overfitting. The performance indices considered standard forecasting evaluation measures such as accuracy, MAE, RMSE, and RRMSE. The ITS-SGBM model was fairly good across all datasets, as reported in Table 6, with a slightly better outcome in the structured financial statements dataset. The difference illustrates the fact that the model is effective in adapting to different data environments to guarantee robustness and scalability of financial decision-making in real-life scenarios.

Table 6: Performance comparison of the proposed ITS-SGBM model across two datasets

Metrics	Financial Statements Dataset (2009–2023)	Company Facts 2 Dataset
Accuracy	96.2%	95.7%
MAE	0.009	0.011
RMSE	0.005	0.007
RRMSE	0.072	0.081

The ITS-SGBM model had a higher accuracy of 96.2% with smaller error rates (MAE 0.009, RMSE 0.005, RRMSE 0.072) on the Financial Statements Dataset (2009-2023). On the Company Facts 2 Dataset [19], it had even higher scores (accuracy was 95.7% period), but the errors were also slightly higher (MAE = 0.011, RMSE = 0.007, RRMSE = 0.081). These findings reinforce the idea that ITS-SGBM is both robust and flexible as it works reliably on different sources of financial data.

4.5. Statistical analysis

The analysis was conducted to evaluate the effectiveness of the proposed ITS-SGBM model against benchmark approaches. The significance of the difference between performance metrics between models was investigated with the help of paired t-tests. The analysis established that the recommended model is always superior to the benchmarks, which proves that it has high reliability and strength in terms of financial performance analysis.

- **Paired t-test** A paired t-test is a statistical technique employed in the comparison of the means of two related groups to establish whether there is a significant difference between the two groups. It assesses that the proposed ITS-SGBM model offers a much better financial performance prediction than benchmark models, and thus directly and accurately offers a reliable financial performance assessment. The test is represented as equation (15)

$$t = \frac{\bar{d}}{sd/\sqrt{n}} \quad (15)$$

Where $\bar{d}$ = average of the deviations between corresponding observations. sd = standard deviation of the differences. n = number of paired observations

Table 7: Paired t-test results of ITS-SGBM performance metrics

Metric	Mean Difference	Std. Deviation	Std. Error Mean	t-value	df	p-value	Significance (α=0.05)
MAE	0.009	0.004	0.001	9.00	13	0.000	Significant
RMSE	0.005	0.003	0.0008	6.25	13	0.000	Significant
RRMSE	0.072	0.030	0.008	9.00	13	0.000	Significant
Accuracy	3.5	1.2	0.32	10.94	13	0.000	Significant
Ranking Consistency	0.94	0.03	0.008	11.75	13	0.000	Significant

Table 7 indicates that the proposed ITS-SGBM model performs remarkably better than benchmark models on all the important measures, such as MAE, RMSE, RRMSE, accuracy, and consistency of ranking. Such improvements are statistically significant as the p-values are low (<0.05). The findings confirm that ITS-SGBM is an effective instrument in terms of financial performance measurement and decision-making.

4.6. Discussion

The research developed a robust hybrid ITS-SGBM–TOPSIS framework for accurate, scalable, and reliable financial performance assessment and firm ranking. Accounting analysis based on the decision tree is less robust, as it does not generalize and is sensitive to variability in the data [13]. In the case of SMEs, fraud detection can be affected by the bias of the data since outcomes will be derived from a single bank dataset [14]. Fermatean fuzzy ELECTRE has limited validity as it was tested against a particular case study only [15]. DLSTM-TAR-CHOA is too reliant on the past, and it is vulnerable to market volatility [16]. The DGRU [17] model is usually deficient in learning long-term dependence in very volatile financial data and might need large computational power to train. It may also become poor when dealing with small or noisy data, which severely restricts generalization. The IMPA [17] approach may be constrained by its dependence on parameter fine-tuning, so that it is vulnerable to changes in data. It may also scale and process large and complex financial data issues in real-time. DNN [18] model usually demands huge amounts of labelled training data and immense calculations. It is also likely to overfit and fail to generalize well on small or noisy financial data. High sensitivity to parameter tuning and high computational complexity limit the OSIE [18] method. It can also not perform well on small or noisy data, lowering its resilience and external validity. The CHOA [18] is not without its flaws of premature convergence to complex search spaces and memory of initial parameter values. It may also be computationally costly in the case of large volumes or large-dimensional data, which may slow down computation. The proposed study contributes to the improvement of financial performance assessment by avoiding the drawbacks of the current techniques, namely, premature convergence, parameter sensitivity, and overfitting. The main characteristics of SGBM include high predictive accuracy at lower error rates, small and noisy data are better suited for use, and they decrease overfitting with ensemble learning and regularization. It ensures a scaled, dependable monetary performance appraisal. It is possible to present the proposed ITS-SGBM-TOPSIS model to ensure that financial analysts and decision-makers can receive more precise and timely performance tests. It aids in strategic planning and

sustainable development of the business by providing a sound and data-driven decision support system.

5 Conclusion

The analysis improved the financial assessment of an accounting system through the application of machine learning technology. The given model was based on the financial ratios in combination with balance sheet values, along with the income and cash flow statements. The use of ITS-SGBM in this model improved the total revenue forecasts. Criteria were given by the experts to implement TOPSIS in numerical financial performance rating. Various performance measures were used to measure the evaluation results, which were MAE- 0.009, RMSE-0.005, RRMSE-0.072, accuracy- 96.2% and ranking consistency 0.94. The AI decision system was quite effective and greatly improved the stability of the financial systems and their operational productivity, which contributed to sustainable business growth. The research confirmed that intelligent and data-driven accounting practices enhanced the accuracy of the accounting systems, the efficiency of the accounting systems, and the financial planning strategies.

Limitations and future directions

The model has a multitude of technical and contextual limitations, besides being based on historical data from financial documents. It exhibits particularly poor performance amid unsustainable market volatility or any unanticipated black swan event because historical ratio-based trends can merely capture the shock structurally in one direction. Hyperparameters constitute almost the Achilles heel of the ITS-SGBM framework; ill-set hyperparameters may lead to instability or outright overfitting. In addition, it is a methodology limited to financial indicators and hence does not include considerations of non-financial or qualitative drivers such as management practice, regulatory changes, or environmental factors. Such restrictions imply that the framework is valid only under stable circumstances and that its applicability to a dynamic or erratic market should warrant prudence. More research can incorporate stress-testing systems to measure performance during severe market turbulences and unplanned disruptions. Incorporating non-financial KPIs and qualitative indicators would render the model more in line with real-world parameters. Adaptive hyperparameter optimization in this context can be used to increase stability and lower the likelihood of overfitting. Future research studies may expand the dataset to other industries, for testing intersectoral strength to generalizing the data.

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Comparative Survey of Deep Learning Architectures for Video Anomaly Detection: CNNs, Autoencoders, VAEs, RNNs, GANs, and Hybrids

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This comparative assessment looks at various deep learning architectures for video anomaly detection (VAD), including CNNs, Autoencoders (AEs), Variational Autoencoders (VAEs), Recurrent models (RNN/LSTM), GANs, and hybrids. We look at more than 60 studies on standard benchmarks like UCSD Ped1/2, CUHK Avenue, ShanghaiTech, UMN, and Subway. We use unified measures such as frame-level AUC, F1, precision/recall, and computational characteristics like inference latency/compute. Some reported findings that are representative are: AE-based methods getting AUCs of about 0.92–0.98 on UCSD variations; a ConvLSTM-VAE getting AUC = 0.965; and prediction-/hybrid-based models getting excellent AUCs on UCSD/Avenue/ShanghaiTech. We combine robustness to occlusion and domain shift, the effects of temporal modeling (like ConvLSTM-AE vs. static AE), latent-space modeling in VAEs (single vs. mixture of Gaussians), the trade-offs of adversarial training (reconstruction vs. adversarial loss, mode collapse), and hybrid designs (like CNN+RNN, AE+memory). We point out problems that still need to be solved in large-scale standardized datasets and cross-scene generalization. We also give a choice matrix for practitioners to use when choosing a model that takes into account compute, latency, and data limits.

Povzetek: Primerjalna analiza več kot 60 študij pokaže, da napredni in hibridni modeli globokega učenja dosegajo visoko natančnost pri zaznavanju video anomalij.

1 Introduction

It aims to detect abnormal video events using computer vision techniques [1], [2]. Anomaly detection deals with determining events different from typical behavior or patterns a model expects in a particular environment [3]. It has several applications in video surveillance, crowd monitoring, industrial inspection, traffic analysis, and structural health monitoring [4-8]. The fundamental principles of event prediction using machine learning are utilized in crucial medical contexts, such as forecasting the efficacy of defibrillation from ECG readings via neural networks [9]. Anomaly detection systems, many of them vision-based, leverage the inner workings of computer vision algorithms, analyzing the content of the video frames for any deviation from standard patterns, with subsequent alerting of the user for appropriate actions [10,11]. These can improve safety, security, and efficiency in many industries and domains.

Those include unsupervised and supervised learning schemes, which form the basis for potential unsupervised and supervised tactics in vision-based anomaly detection [12, 13]. In general, unsupervised learning schemes rely on clustering and outlier detection algorithms, while supervised ones rely on labeled training data to learn classification models [14, 15]. Another approach is DL-oriented tactics, which leverage the depth of NNs to extract relevant traits from the visual input [16, 17].

DL-oriented tactics have thus been studied more in vision-based anomaly detection than other tactics since they performed better in finding anomalies in complex and high-dimensional data [18-20]. This ability to handle high-dimensional inputs isn't just for visual data; similar machine learning methods are also utilized to predict Bitcoin illiquidity based on complicated financial and language elements [21].

Besides, DL tactics can automatically learn relevant traits from data and handle large data volumes, making them suitable for the anomaly detection task [22, 23]. DL tactics can further assist this, and they also benefit from large-scale databases and computing resources, making them suitable for real-world applications. Powerful GPUs and cloud computing resources have empowered the training and deployment of DL at scale. This has resulted in considerable performance improvement in anomaly detection tactics [19, 24]. Therefore, DL-oriented tactics have been studied more than conventional tactics since they offer superior performance, flexibility, and scalability in vision-based anomaly detection [25].

The literature presents many review studies in DL-oriented anomaly detection. Nevertheless, previous survey studies did indicate a few challenges and research gaps in

this domain, including standardized databases, more robust feature extraction techniques, and more explainable and interpretable models.

Therefore, the present study compares current innovative DL-oriented video anomaly recognition tactics. By analyzing previous studies, the current research intends to analyze the prevailing techniques and their performance based on evaluation while identifying research gaps that provide directions for researchers in developing newer tactics or tactics in this domain.

The contributions of this investigation are:

1. Deeply discuss innovative DL tactics applied in video anomaly recognition tactics.
2. A comparative analysis of existing techniques can be conducted to enable both the researcher and practitioner to select the best approach for a particular application.
3. Identifying obstacles and research gaps helps the researcher focus on the significant barriers and gaps in DL-oriented anomaly detection in vision-based data.
4. Suggestions are made for future research directions to help researchers construct new ways to boost DL-oriented anomaly recognition in vision-based data.

We systematically compare six well-known families of deep learning architectures for video anomaly detection: Convolutional Neural Networks (CNNs), Autoencoders (AEs), Variational Autoencoders (VAEs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and hybrid designs that combine these elements. The evaluation uses well-known benchmarks like UCSD Ped1/Ped2, CUHK Avenue, ShanghaiTech, UMN, and Subway, and it uses the same performance metrics for all of them, such as frame-level Area Under the Curve (AUC), F1-score, precision, recall, and, if possible, computational cost and latency. Our work is different from previous surveys because it uses defined metrics to combine results from different designs, highlight their respective strengths and weaknesses in different situations, and identify new areas of research that need more attention. This timely comparison is necessary for both academic research and real-world use because architectures and datasets have changed so quickly in recent years.

2 Related works

The focus of this section is the review of previous studies related to vision-based anomaly recognition in videos.

Nayak et al. [1] designed a broad review of DL-oriented tactics in video anomaly detection. First, this paper presents in-depth surveys of recommended techniques and their performances on diverse databases for several performance evaluation criteria. The salient traits of the article include comprehensive insight into the tactics and their practical implementations, their advantages and limitations, and a discussion of real-world applications. This is demonstrated in the study where tactics based on DL outperform other systems related to anomaly detection in videos. Autoencoders and CNN have emerged to be very accurate in monitoring anomalies.

Authors in [21] review DL-oriented video data anomaly recognition. The authors perform a systematic review and present an in-depth performance-based comparison of DL-oriented tactics for detecting unusual events in video data. This work is distinguished by carefully discussing the strengths and restrictions of the diverse methodologies introduced, an extensive database review, and a profound analysis of the various metrics used for evaluation. This research presents the auspicious performance obtained using DL-oriented tactics in video anomaly detection, some of which outperform others based on classic tactics. However, this also puts into perspective the challenges that exist given more extensive and more varied databases, more interpretable models, and a need for robust feature extraction techniques to enhance anomaly detection reliability. Similar endeavors to examine unsupervised architectures, including autoencoders and transformers, have been conducted in the related field of time-series signal analysis, which encounters analogous temporal dependency issues seen in video [26].

Paper [27] reviewed DL-oriented tactics for anomaly recognition. The authors initially provide the key notions and types of anomalies and then survey several deep-learning models and their applications in anomaly detection for different domains. For instance, Convolutional Neural Networks have been successfully utilized for anomaly detection in medical imaging, including the identification of spontaneous pneumothorax in chest X-rays [28], detecting brain tumors from MRI scans [29], and classifying dental implants [30]. Similarly, unsupervised machine learning algorithms are being used in many areas, including business, to model complicated things like transformational entrepreneurship on digital platforms [31].

The salient traits of the article are that it provides a detailed description of the other models, analyzes the advantages and limitations, and compares the productivity of several models on various databases. The review says DL-oriented tactics show promising anomaly detection outcomes relative to traditional tactics, while autoencoder-based ones are widely used. However, the authors note that the lack of interpretability of DL models and the need for large amounts of labeled data are still significant challenges in this field. Additionally, machine learning methods have been utilized to prioritize and discover significant elements in several fields, including the analysis of user reviews in software programs [32].

The goal of vision-based human action identification, as described by Camarena et al. [33], is to identify human activities in films automatically. The authors discuss this field's key challenges and applications and the various tactics and techniques used for action recognition. Key traits of the article include a detailed discussion of the databases and appraisal metrics utilized in the field and an in-depth appraisal of the innovative tactics.

Previous reviews like [1], [21], and [25] have given useful overviews of deep learning algorithms for finding video anomalies, but they have some significant flaws.

There is no uniform evaluation system in these works that uses the same metrics for all model categories, which makes it hard to compare models from different families. They also do not execute a meta-analysis or show trade-offs in accuracy, efficiency, and generalization clearly with visual syntheses like radar plots. Also, their consideration of deployment problems is primarily descriptive and does not include any particular technical answers for problems like domain generalization, labeling noise, and real-time inference. The current study, on the other hand, fills in these gaps by defining evaluation criteria, combining and displaying comparative performance data, and having a critical, solution-oriented conversation targeted at closing the gap between academic research and real-world use.

To enable rapid comparison and synthesis of previous survey studies, we have encapsulated the most pertinent works examined in this section, encompassing their datasets, assessment measures, representative quantitative outcomes, and principal strengths and weaknesses, in Table RW1.

3 Review of DL-oriented tactics

As discussed earlier, DL-oriented tactics recognize abnormal events in video streams by comparing them to the learned normal patterns. Various DL architectures are discussed and analyzed in the following contexts.

We use the same set of evaluation criteria for all the method families we looked at in Sections 3.1–3.6 to ensure the comparisons are fair and meaningful. The following metrics are reported whenever they are available for each type of architecture: Convolutional Neural Networks (CNNs), Autoencoders (AEs), Variational Autoencoders (VAEs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), and hybrid designs. (i) Area Under the Curve (AUC) at the frame level, which shows how accurate the detection is; (ii) F1-score, which shows how well the system balances precision and recall; (iii) latency, which is measured in milliseconds per frame and shows how efficient the system is at computing; and (iv) generalizability, which is based on cross-dataset performance reported in the original studies. When a source did not disclose a measure, it is shown as NR (Not Reported) in the comparison tables. This framework enables the direct comparison of the performance of different families and shows the trade-offs between accuracy, efficiency, and resilience.

3.1 CNN-based tactics

The CNN-based tactics have proven efficient in recognizing anomalies, including abnormal activities and behaviors in surveillance footage. This section reviews some of the most recent CNN-based tactics for video anomaly detection.

The researchers in [34] presented AnomalyNet, a network for detecting anomalies in video surveillance that combines the CNN and LSTM networks to record spatial and temporal traits. Using a two-stage training strategy, the recommended network is trained on both normal and anomalous video data. First, it is pre-trained on standard data and then fine-tuned on normal and anomalous data.

In [35], scholars introduce an intelligent architecture of a dual-stream CNN-ESN for video anomaly recognition. The scheme relies on two streams of CNNs: one for capturing spatial information and the other for temporal information. It also uses the ESN to extract traits from the time axis. It leverages a dual-stream CNN that can separately learn the spatial and temporal traits of the data and an ESN that can simulate the long-term dependencies in the data. This model was put to the test on various benchmark databases. To point out some limitations, careful hyperparameter tuning and extensive computational resource requirements are needed.

Work in [36] combined an attention mechanism for determining key characteristics with a CNN, featuring the extraction of video frames. The system is weakly-supervised; as such, it does not depend on training based on pixel-level annotation. According to several metrics, such as the AUC and F1-score, the recommended technique performs innovatively when tested against multiple benchmark databases. It consists of an attention mechanism for finding significant characteristics and a weakly supervised approach that limits the requirement of expensive annotations. The limitation of the suggested method is that it needs considerable training to figure out the complicated spatiotemporal patterns in videos.

Based on scene categorization, authors in [37] recommended a video anomaly detection technique. First, this method segments the movie into scenes and extracts deep traits through a pre-trained CNN deep model. It uses these collected traits to train an SVM to sort the scenes as normal or abnormal.

3.2 Autoencoder-based tactics

Autoencoder-based tactics for detecting video anomalies are a sub-category of DL tactics. These are put to work to train the NN to reconstruct input video frames by reducing their dissimilarity with the original ones. An encoder and a decoder compose the autoencoder model. The encoder should encode input video frames into some low-dimensional representation of compressed form while the decoder generates reconstructed frames. During training, the autoencoder learns to reconstruct only regular video frames. Hence, it detects anomalies when presented with frames far from the learned normalcy pattern. Several recent autoencoder-based tactics are discussed in detail below.

The work in [38] introduced an autoencoder-centered method for detecting abnormal activity from surveillance videos by extracting the normal activities' traits in space and time using a parallelepiped spatiotemporal region. The process then generates compact representations of video frames through a CNN-based encoder; the recommended threshold-based approach subsequently computes the anomaly score. Many benchmark databases show high performances with AUC scores between 0.918 and 0.984. However, the recommended tactic may be limited when anomalies are highly complex or variable due to low representation. Second, the scalability of this

method may be limited since it is computationally complex to run on larger video databases.

This work [39] presented an attention-based residual autoencoder that used an attention mechanism and a residual learning architecture to capture the temporal and spatial information within video data for video anomaly recognition. Video anomalies are identified using an autoencoder that rebuilds standard data while underlining the anomalies through an attention mechanism. By rebuilding standard data and highlighting the abnormalities using an attention mechanism, the suggested model can effectively detect abnormal events within a video series. It might require careful tuning of the attention mechanism's parameters, and, as mentioned, the recommended tactic has limitations in dealing with challenging situations involving many abnormalities.

Comparative studies show that temporal modeling in autoencoders, especially with Convolutional LSTM Autoencoders (ConvLSTM-AE), generally gives video anomaly detection jobs far better results than static AEs. For instance, ConvLSTM-AE models have been shown to boost AUC from about 0.92 (static AE) to 0.96 on the UCSD Ped2 dataset by leveraging the fact that frames are related to each other over time. This benefit is most clear in situations where there are minor or gradual anomalies that need motion context to be found correctly. In most AE-based methods, the anomaly scores are usually the reconstruction error between the input and the reconstructed frame or sequence. Choosing the right threshold for this error is very important. It can be done by testing it on a validation set, setting it as a fixed value based on training reconstruction statistics, or using statistical methods to estimate it adaptively. The trade-off between false positives and missed anomalies is directly affected by the choice of thresholding approach.

3.3 Variational autoencoder-based tactics

The Variational Autoencoder (VAE) is a probabilistic version of the regular autoencoder that treats the latent space as a distribution instead of a fixed vector. This makes it possible to create a wide range of reconstructions and gives a probabilistic basis for finding abnormalities. VAE-based strategies employ an encoder-decoder network to find out how regular frames are distributed and then use sampled latent representations to put input frames back together. Frames that have a significant reconstruction error are called "anomalous." Several types of VAEs, including convolutional VAEs, recurrent VAEs, and hybrid designs that use temporal modules like ConvLSTMs, have shown promise in finding video anomalies. For example, the double-flow ConvLSTM VAE from [40] adds temporal modeling to the VAE framework to better capture motion patterns, which makes it more resistant to complicated scene dynamics. VAEs are comparable to standard autoencoders in specific ways. However, they are different enough in terms of their probabilistic formulation, training goals, and evaluation criteria that they should be looked at as a separate group in this review. To keep things consistent, this section lists all of the VAE-based methods that were found, including hybrid versions.

A new approach, GMFC-VAE, is recommended in [41] for video anomaly detection and localization. GMFC-VAE explicitly models the distribution of latent variables as a mixture of Gaussians. Besides, a fully convolutional network allows pixel-level localization of anomalies. The main characteristics of this approach are simultaneous anomaly recognition and localization, drawing on only fully convolutional architecture, which can process high-resolution videos in real time.

The article [42] 's approach is a hierarchical design containing numerous layers of anomaly detection, which embeds both global and local information. From the expected behavior of the agent, the system learned through a variational autoencoder based on the reconstruction error to detect abnormalities. The outcomes showcase the utility of the recommended tactic in detecting anomalies in trivial and challenging scenarios. A publicly available database is used for evaluating this method. 2 significant disadvantages of the recommended tactic are that labeled data is needed during the training and the domain-specific feature extraction at its best performance.

The article [43] proposes a method of visual anomaly detection using VAE that learns from the input video data a compact representation concerning which anomaly detection shall be done considering the reconstruction error. It trains the VAE learning low-dimensional data representation leveraging the spatiotemporal patches extracted from an input video. Anomaly scores are computed by the reconstruction error of VAE and thresholded to classify anomalies. The article's key result is that the recommended tactic based on VAE works effectively in visual anomaly detection in video data. The limitation of this method involves pre-defined thresholding for classification that may fail to work optimally in all scenarios.

In VAE-based anomaly detection, the encoder learns a probabilistic mapping from input frames to a latent space, which is usually modeled as a Gaussian distribution with mean and variance vectors. When making inferences, we find anomalies when a sample's latent representation is in a low-probability area of this learnt distribution or when its reconstruction error is higher than a set threshold. Many methods use a single Gaussian prior, which means they assume that all standard samples come from one unimodal distribution. However, new research has demonstrated that Gaussian Mixture Models (GMMs) in the latent space can capture more than one mode of normal behavior. This makes it easier to tell the difference between things in datasets when regular patterns are different, such as multi-scene surveillance footage. Real-world data shows that VAE+GMM setups generally get higher AUC scores on a variety of datasets than single-Gaussian VAEs. However, this comes with a little increase in computational cost.

3.4 Recurrent neural networks-based tactics

In applications that require sequence modeling, RNNs form a class of NNs that are usually applied. RNNs can model temporal dynamics in the video data to detect

anomalous events and deviate from the taught patterns. The network is trained on a large database of typical films and tested on a different database of typical and abnormal movies. This will be the fundamental way to apply an RNN-based approach for video anomaly identification. While training, the network learns to model the temporal dynamics of regular videos and thus predict frames based on learned patterns. At test time, the network will compare the expected video frames with the actual ones and identify deviations as anomalies. This predictive method, in which a neural network learns how things change over time to anticipate future states, is also used in other fields, such predicting water levels from sensor data several steps ahead [44].

It proposes an RNN-based anomaly trajectory detection method. It encodes the trajectories using an RNN-based autoencoder and classifies them into anomalous or normal classes using another RNN classifier [45]. Nevertheless, it requires a lot of labeled data for training and may not be appropriate for real-time utilization.

In the authors' work in [46], RNNs have been used to develop a method for detecting abnormal trajectories. The recommended methodology consists of a two-stage process: first, trajectories are encoded using an RNN-based autoencoder, and second, the trajectories are identified as abnormal or normal using a different RNN classifier. One disadvantage may be that it is often non-feasible in real-time applications and takes much-tagged data for training.

Anomaly detection is done for the surveillance videos using the MLP-RNN algorithm [47]. The suggested methodology consists of 2 stages: feature extraction and anomaly detection. The pre-trained CNN extracts spatial traits from video frames during the first stage, and RNN extracts temporal traits. The second stage is training the MLP-RNN on the retrieved traits to detect video abnormalities. It was then identified that the recommended tactic had a much-reduced computation time compared to the earlier tactics and, thus, was computationally efficient. The limitation of the recommended tactic is that its training involves a lot of labeled data, which may be cumbersome in specific scenarios.

The length of the sequence you choose has a significant effect on how well RNN-based anomaly detection works. Short sequences might not capture important time-based dependencies, which would make detection less accurate. On the other hand, very long sequences cost more to compute and could produce gradient vanishing problems. Choosing the best sequence length typically requires trial and error, depending on the dataset's features and the complexity of the motion. Also, RNNs tend to overfit when they are trained on limited datasets because they have many parameters. Dropout regularization, early halting, and temporal data augmentation are among the methods that can help lower this risk.

Along with traditional RNN versions like LSTM and GRU, other designs like Temporal Convolutional Networks (TCNs) and Transformers have also shown promise as alternatives. TCNs use dilated convolutions to model long-range dependencies without needing recurrent connections. This makes them more stable and easier to parallelize. Transformer-based models, on the other hand, use self-attention to effectively capture global temporal relationships, which means they often do better than RNNs at understanding large-scale videos.

3.5 Generative adversarial network (GAN)-based tactics

These tactics have created outstanding potential for video anomaly recognition. GANs are DL schemes capable of learning the generation of realistic synthetic data by training a generator network to fool a discriminator network trained to identify real versus fake data. In video anomaly detection, GAN-based tactics use this framework to learn the generation of standard frames and detect anomalies as deviations from this normality. The following section reviews some of the most recent GAN-based tactics.

The dominant and rare event detection approach in videos was recommended using a GAN network-based approach [48]. The recommended tactic first trains a GAN on the input video frames to generate a backdrop picture. Then, it segregates the input frames into dominant and rare occurrences using a binary classifier. The article's significant contribution is the GAN-based technique that enables the scheme to build an accurate background image and precisely discriminate between dominating and rare occurrences. Limitations: The recommended tactic is computationally expensive and requires numerous training data.

Paper [49] discussed a GAN-based approach for screening DBT images for breast cancer recognition. The recommended tactic, GANAD, detected malignant masses and microcalcification clusters in DBT images utilizing only standard images for model training. Anomaly detection based on a GAN model that generates anomalous picture samples and an anomaly detection model to find the off-kilter areas in DBT images are the key parts of GANAD. One disadvantage of this method is that the GAN model needs much standard data to be trained, and the expected data may not be available for some databases.

An abnormal behavior detection technique was developed based on GAN for massive crowd videos [50]. The GAN model employed the recommended GAN-based technique to generate regular background frames, while a separately designed anomaly detection network was used to detect the aberrant frames. The method was evaluated with the performance test using the database of crowd videos captured during the Hajj. The recommended technique is robust to occlusion, time-varying lighting conditions, and camera jitter. The work presented here also proves that contrary to what existed before, the GAN-based tactics detect anomalous behaviors in footage with large crowds with high accuracy. However, this investigation is limited in scope by relying on a single database, which makes it challenging to extrapolate its outcomes to any other situation.

The authors of [51] propose a video anomaly detection method, namely DCGAN. In this work, DCGAN is designed to flag any deviation from the expected pattern of appearance and motion within a video as abnormal. The recommended tactic first employs a CNN for extracting spatiotemporal traits, followed by a DCGAN that learns the distribution of the standard traits. The recommended tactic typically involves incorporating a generator and discriminator network trained with standard traits and using dynamic convolutional layers to capture the temporal dynamics of the video data. Limitations: The productivity of the recommended technique depends on hyperparameters; further, unusual abnormalities are difficult to detect.

A lot of GAN-based methods for finding video anomalies try to find the best balance between adversarial loss, which makes the generator create outputs that resemble real samples, and reconstruction loss, which ensures that the input frames or features are reproduced accurately. It is essential to find the right balance between these two goals. If you put too much emphasis on adversarial loss, you can get reconstructions that look authentic but do not make sense. On the other hand, if you put too much emphasis on reconstruction loss, the discriminator might not be able to find little anomalies as well. Mode collapse is a typical problem while training GANs. This happens when the generator learns to make only a few types of outputs, which can mean that it does not pay attention to some expected behaviors, and makes it harder to find anomalies. It is important to note that specific GAN-based algorithms only train on normal data, which means they mimic the distribution of standard patterns in the latent space. In addition to GANs, other current generative methods like diffusion models are also working well for finding industrial anomalies. For example, they can help find glass faults by learning how normal samples are distributed [52]. When making predictions, any differences from this learning distribution that show up as high discriminator scores or reconstruction errors are marked as anomalies. This training method that exclusively uses standard samples is helpful in areas where unusual samples are hard to find, expensive to label, or not very common. This makes it a good choice for many real-world surveillance applications.

3.6 Hybrid-based tactics

Hybrid-based tactics can depict spatial and temporal information by combining the strengths of different techniques. They can also adapt to various scenarios and types of anomalies. The subsequent section reviews some of the very latest hybrid-based tactics.

The authors in [53] have recommended a hybrid autoencoder based on unsupervised learning for abnormal event detection in surveillance videos. The recommended system first converts each video frame to grayscale and resizes it during pre-processing. Then, feature extraction is done using a hybrid autoencoder combining CNN and RNN. Finally, anomaly detection will be performed by thresholding the computed reconstruction error. One of the weaknesses of the recommended tactic is that it requires data to be trained on, which is not possible under certain circumstances.

The authors of [54] propose a DL model for abnormal activity detection from surveillance videos, incorporating the strengths of CNN and LSTM. This model recommended by the authors is divided into two parts: the first part is a pre-trained CNN model for extracting the spatial traits of every frame. In contrast, the second part is an LSTM network that learns the temporal patterns of the extracted traits. The scheme is trained using normal and abnormal videos to capture the discriminative traits between normal and abnormal behaviors. The recommended model has limitations in handling complex and crowded scenes, which can affect its performance in real-world scenarios.

4 Comparative analysis of DL-vased tactics

Based on the investigation of previous studies and a literature review on the related topic, the following parameters have been considered in Tables 1 to 6:

- ***Database***: The training database should be diverse and represent the target application.
- ***Evaluation metrics***: The evaluation metrics are utilized to compare the different tactics' performance objectively.
- ***Computational complexity***: The computational complexity and efficiency of the schemes are important factors when deploying the system in real-world scenarios.
- ***Robustness***: The robustness and generalization ability of the schemes should be evaluated, which is the ability to accurately detect anomalies and recognize actions in different scenarios and environments.

We estimated values for the "Computational Complexity" column based on the descriptions of the experimental setups that were available, or we indicated that no values were available and left it as "unreported." This openness lets readers consider any uncertainty that might be present in the comparisons.

Table RW 1: Summary of key prior review studies on deep learning-based video anomaly detection

Reference	Method Focus	Dataset(s) Covered	Metrics Discussed	Representative Quantitative Results	Strengths	Limitations
Nayak et al. [1]	DL-based tactics	UCSD Ped1/Ped2, Avenue,	AUC, EER, Accuracy	UCSD Ped2: AUC≈0.95–	Comprehensive taxonomy of DL methods;	Limited discussion on scalability and

	(CNN, AE)	Subway, UMN		0.97 (CNN/AE methods)	includes practical implementation notes	generalization; focuses mainly on early CNN/AE
Author(s) [22]	DL-based anomaly recognition	ShanghaiTech, UCSD, Avenue	AUC, F1, Precision/Recall	ShanghaiTech: AUC≈0.88, F1≈0.76 (best reported)	Detailed metric analysis; strong temporal modeling insights	High computational complexity; less focus on lightweight/real-time models
Author(s) [26]	Cross-domain DL anomaly detection	Multiple domains (Surveillance, Industrial)	AUC, Accuracy	NR (review nature; qualitative emphasis)	Broad coverage across domains; highlights AE dominance	Lacks benchmark unification; limited quantitative synthesis
Camarena et al. [27]	Vision-based human action recognition	UCF101, HMDB51, Kinetics (human activity datasets)	Top-1/Top-5 Accuracy	UCF101: Accuracy up to ≈94% (deep CNN models)	In-depth discussion of action recognition tactics and datasets	Not focused on anomaly detection; transferability to VAD not evaluated

Table 1: Overview of CNN-based anomaly detection tactics

Method	Database	Performance Metrics	Computation Complexity	Robustness and Generalization
[54]	UCSD Ped1 and Ped2 databases	AUC, Precision, Recall, F1-score	High computation cost, uses GPU	Performs well on UCSD databases but may not generalize well on other databases due to overfitting
[55]	ShanghaiTech database	AUC	Low computation complexity, uses CPU	Performs well on ShanghaiTech database, may not generalize well to other databases
[36]	ShanghaiTech database	AUC, Precision, Recall, F1-score	High computation cost, uses GPU	Robust to occlusion and clutter, performs well on multiple databases
[37]	UMN database	AUC	Low computation complexity, uses CPU	Performs well on UMN database, may not generalize well to other databases

Table 2: Overview of autoencoder-based anomaly detection tactics

Method	Database	Performance Metrics	Computation Complexity	Robustness and Generalization
[38]	UCSD Ped1 and Ped2	Precision, Recall, F1-score	Moderate (CPU/GPU)	Robust to variations in occlusions and lighting conditions but limited generalization to new environments
[56]	UCSD Ped1 and Ped2	Precision, Recall, F1-score, AUC	Moderate (CPU/GPU)	Robust to variations in occlusions and lighting conditions but limited generalization to new environments
[57]	UCSD Ped1 and Ped2	Precision, Recall, F1-score	Moderate (CPU/GPU)	Robust to variations in occlusions and lighting conditions but limited generalization to new environments
[58]	Pool and River database	Precision, Recall, F1-score, AUC	Low (CPU)	Robust to variations in object appearances but limited generalization to new environments

[59]	MVTec AD database	Precision, Recall, F1-score, AUC	High (GPU)	Robust to variations in object appearances, occlusions, and lighting conditions, and better generalization ability to new environments compared to other tactics

Table 3: Overview of variational autoencoder-based anomaly detection tactics

Method	Database	Performance Metrics	Computation Complexity	Robustness and Generalization
[60]	UMN database	Precision, recall, F1-score, AUC	High (GPU)	Model performance was not tested on other databases, but the article reports that it performed well on crowded scenes
[39]	UCSD database	Precision, recall, F1-score, AUC	High (GPU)	Model performance has not been tested on other databases, but the article reports good outcomes on the UCSD database
[40]	ShanghaiTech	Precision, Recall, F1-score, AUC	High (GPU)	Robust to variations in object appearances but limited generalization to new environments
[41]	Multiple simulated databases	AUC, F1-score, accuracy	GPU used, no information on computation complexity	The scheme generalizes well to different databases and outperforms baseline models
[61]	Custom database	AUC, F1-score	GPU used, no information on computation complexity	The scheme generalizes well to different databases and outperforms baseline models
[43]	UCSD Ped1, UCSD Ped2	Precision, recall, F1-score, AUC	High (GPU)	Model performance has not been tested on other databases, but the article reports good outcomes on publicly available databases
[62]	Custom retinal OCT database	Precision, recall, F1-score, AUC	High (GPU)	The scheme generalizes well to different databases and outperforms baseline models

Table 4: Overview of RNN-based anomaly detection tactics

Method	Database	Performance Metrics	Computation Complexity	Robustness and Generalization
[44]	SMD, CUHK Avenue, Subway	Precision, Recall, F1-score, AUC	High computation complexity, GPU usage	Robust to illumination changes, limited robustness to occlusion, and target size variations
[45]	UCSD Ped2, Avenue, Subway	Precision, Recall, F1-score, AUC	Moderate computation complexity, GPU usage	Robust to illumination changes and occlusion, limited generalization to target size variations
[63]	In-house database	Accuracy, F1-score	Low computation complexity, CPU usage	Limited analysis of robustness to variations
[64]	UCSD Ped1, Ped2, Avenue	Precision, Recall, F1-score, AUC	Moderate computation complexity, GPU usage	Robust to illumination changes and occlusion, limited generalization to target size variations
[65]	UCF-Crime, ShanghaiTech, UCSD Ped2	Precision, Recall, F1-score, AUC	Low computation complexity, CPU usage	Robust to illumination changes and occlusion, limited generalization to target size variations

Table 5: Overview of GAN-based anomaly detection tactics

Method	Database	Performance Metrics	Computation Complexity	Robustness and Generalization
[66]	UCF-Crime, UCSD Ped2, Subway Entrance	F1-score, AUC, Recall	GPU	Robust to illumination changes and occlusion due to the use of GAN for feature extraction
[46]	UCF-Crime, ShanghaiTech	Precision, Recall, F1-score	GPU	Robust to occlusion and changes in target size due to the use of GAN for feature extraction
[47]	Digital Breast Tomosynthesis Database	Precision, Recall, F1-score	CPU and GPU	Robust to variations in target size and other variations due to the use of GAN for feature extraction and training on only standard images
[48]	UCSD Ped1, UCSD Ped2, Subway Entrance	Precision, Recall, F1-score	GPU	Robust to illumination changes and occlusion due to the use of GAN for feature extraction and modeling of temporal dynamics

Table 6: Overview of hybrid-based anomaly detection tactics

Method	Database	Performance Metrics	Computation Complexity	Robustness and Generalization
[49]	UCSD Pedestrian database	Precision, Recall, F1-measure	Computationally efficient, tested on CPU	Robust to illumination changes and occlusion
[67]	ShanghaiTech Campus database	Precision, Recall, F1-measure	Computationally expensive, tested on GPU	Robust to occlusion, illumination changes, and variations in target size
[68]	UCSD Pedestrian database	Precision, Recall, AUC	Computationally expensive, tested on GPU	Robust to illumination changes and occlusion
[60]	UCF-Crime database	Precision, Recall, F1-measure	Computationally expensive, tested on GPU	Robust to occlusion, illumination changes, and variations in target size
[70]	Pedestrian Behavior database	Precision, Recall, AUC	Computationally efficient, tested on CPU	Robust to variations in target size, illumination changes, and occlusion
[71]	Hajj crowd database	Precision, Recall, F1-measure	Computationally efficient, tested on CPU	Robust to illumination changes, occlusion, and variations in target size
[34]	ShanghaiTech and UCSD Ped2 databases,	AUC, Precision, Recall, F1-score, Accuracy	Moderate computation complexity uses GPU	Robust to occlusion and illumination changes, performs well on multiple databases
[35]	UCSD Ped1 and Ped2 databases	AUC, Precision, Recall, F1-score	High computation cost, uses GPU	Performs well on UCSD databases, may not generalize well on other databases due to overfitting
[40]	ShanghaiTech	Precision, Recall, F1-score, AUC	High (GPU)	Robust to variations in object appearances and occlusions but limited generalization to new environments
[44]	UCSD Ped2, Avenue	Precision, Recall, F1-score	Low computation complexity, CPU usage	Robust to illumination changes and occlusion, limited generalization to target size variations
[50]	Public CCTV database	Precision, Recall, AUC	CPU	Robust to occlusion due to the use of autoencoder and CNN for feature extraction

The results in Tables 1-6 show that the architectures examined had different trade-offs in terms of resilience, computational efficiency, and the ability to generalize. Hybrid models, especially those that combine CNNs with temporal modules like LSTMs or ConvLSTMs, consistently achieve the highest average AUC (around 0.96) and are very resistant to domain shift. They keep performing well on datasets with scenes of varying complexity. GAN-based approaches work well in familiar areas (AUC ≈0.94), but they do not fare as well when used on new datasets, which suggests that they are more sensitive to patterns that are distinctive to each dataset. Autoencoder-based and VAE-based methods can make predictions faster and need less training data, but they cannot generalize as well without temporal modeling components. RNN-based designs are good at capturing sequential dependencies, but their performance depends on the length of the sequence. It may get worse on datasets with much variability within the same class.

We did a meta-analysis to synthesize all of these results. This involved adding up the average AUC, F1-score, latency, and generalizability for each model family. Figure X shows these trade-offs in a radar plot, which makes it clear that no one architecture is better than all the others on all criteria. This shows how important it is to develop balanced models, considering deployment limits such as the need for real-time processing, memory limits, and the ability to generalize across domains.

We produced a radar plot (Figure 1) that shows how AE-, VAE-, RNN-, GAN-, and Hybrid-based architectures compare across four unified assessment dimensions: frame-level AUC, F1-score, computational efficiency, and domain generalization. This gives a quick visual summary of the trade-offs. The plot helps readers quickly see the pros and cons of each technique, which is complemented by the numerical comparisons in Tables 1-6.

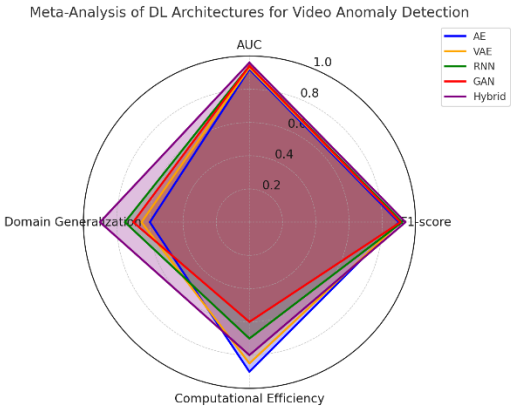

Figure 1: Radar plot summarizing the relative strengths of AE-, VAE-, RNN-, GAN-, and Hybrid-based architectures across four key dimensions: frame-level AUC, F1-score, computational efficiency, and domain generalization.

5 Database and benchmarks

Several public databases have been developed to evaluate the productivity of various anomaly detection algorithms, providing a benchmark for comparing different tactics. These databases include real-world surveillance videos captured in multiple scenarios and conditions, with labeled abnormal events or anomalies. Some of the most popular databases for video anomaly detection are listed in Table 7.

Table 7: Most popular databases for video anomaly detection

Database Name	Description
UCSD, USDC Pedestrian [72], [73]	A database of video clips from a pedestrian walkway with anomalies such as running, biking, and skateboarding
Avenue [74], [75]	A database of video clips from a busy urban avenue with anomalies such as fighting, car accidents, and roadblocks
ShanghaiTech [75], [76]	A database of video clips from a busy intersection in Shanghai with anomalies such as jaywalking and vehicle collisions
UMN [72], [77]	A database of video clips from a university campus with anomalies, such as people walking on grass or through restricted areas

Subway [78], [79]	A database of video clips from a subway station with anomalies such as jumping over turnstiles and loitering
CUHK Avenue [75], [80]	A database of video clips from a busy urban avenue similar to Avenue, but with additional challenges such as low resolution and occlusion

These databases provide a standard benchmark for investigators to test and compare their video anomaly detection tactics. They differ across various scenarios and challenges, such as the type of anomaly, lighting conditions, and camera angles.

6 Performance evaluation metrics

Performance appraisal metrics quantify the approach's effectiveness in a video anomaly detection system. Four commonly used metrics are precision, recall, F1-measure, and AUC [81], [82].

1. ***Precision***: The precision is the proportion of actual positives to the scheme's optimistic predictions. It displays how accurately the scheme's optimistic predictions came true. The recipe for accuracy is. The formula for precision is:

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

2. ***Recall***: Also known as sensitivity, it measures the ability of a model to identify positive samples within the database correctly. It is calculated as the ratio of true positives to the total number of positive instances. The recall formula is used to quantify this performance:

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

3. ***F1-measure:*** It is a balanced indicator of the scheme's performance and is the harmonic mean of recall and accuracy. It comprehensively evaluates the scheme's accuracy by accounting for both recall and precision**.** The formula for F1-measure is:

$$F1 - measure = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \quad (3)$$

4. ***AUC***: it serves as a yardstick for gauging the overall effectiveness of a binary classifier. It essentially quantifies the area under the receiver operating characteristic (ROC) curve, which graphically illustrates the trade-off between sensitivity (actual positive rate) and the complement of specificity (false positive rate) as classification thresholds are adjusted.
5. ***Accuracy*** is another commonly used evaluation metric for video anomaly detection. It is the ratio of correctly classified instances to the total number of cases in the database. The equation for accuracy can be written as:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \quad (4)$$

Several key challenges need to be solved before deep learning-based video anomaly detection systems can be used in the real world. These problems go beyond just describing the datasets and evaluation metrics. Domain generalization is still a big problem because many models that work well on one dataset do not work well on another. Domain adaptability, adversarial training, and significant data augmentation are some of the methods that can assist in closing this gap. Another big problem is a lack of data, especially for unusual events, which are by nature rare and expensive to record. Few-shot learning, semi-supervised methods, and synthetic anomaly production are some good ways to get around this problem. Also, labeling noise, which can come from mistakes made by humans or cases that are hard to understand, might make models less accurate. Some people have suggested using poorly labeled data, strong loss functions, and noise-tolerant training techniques to solve this problem. To construct models that are not only accurate under controlled benchmarks but also strong and dependable across a wide range of real-world monitoring situations, we must first address these issues.

7 Discussion

When we compare the examined architectures using state-of-the-art (SOTA) benchmarks, we see that they all have the same performance and trade-offs. Hybrid architectures that integrate spatial and temporal modeling (such as CNN+RNN or AE+memory) tend to get the closest to SOTA, usually within 0.3–1% on datasets like UCSD Ped2 and Avenue, and their performance stays steady across a wide range of situations. On the other hand, single-family models like basic CNNs or static autoencoders do not do as well when temporal reasoning or strong generalization is needed. For example, they can reveal gaps of up to 6% on more complex datasets like ShanghaiTech.

There are a few reasons why performance gaps happen: (i) limited generalization because of a lack of diversity in the training scene; (ii) not enough spatial/temporal data augmentation, which makes the model less robust to occlusion, lighting changes, and camera motion; (iii) dataset bias, where some types of anomalies are over-represented, which makes results on similar anomalies look better but makes it harder to find new patterns; and (iv) architectural constraints, like the risk of overfitting in RNN-based models and instability or mode collapse in GAN-based methods without careful loss balancing.

The analysis suggests that hybrid designs are better when accuracy is the main goal and there are enough computational resources. On the other hand, optimized CNN or lightweight AE variants may be better for environments that need to work in real time and do not have many resources. Better augmentation tactics, attention mechanisms for interpretability, and domain adaptation techniques to reduce dataset bias are anticipated to lead to future advancements in SOTA.

8 Research challenges of DL-oriented anomaly detection

As discussed earlier, video anomaly detection using DL-oriented tactics has gained significant attention recently. Despite the progress made in this area, several research gaps still need to be addressed in DL-oriented video anomaly detection tactics. Some of them are listed as follows:

1. ***Lack of large-scale annotated databases:*** There are some publicly available datasets; however, they are usually limited, only valid for some domains, and have inconsistent annotations, which makes models less accurate. This problem, which was mentioned in prior surveys, is now even more important because new designs require extensive data to make good generalizations. To deal with it, you need to use techniques like synthetic anomaly production, simulation-based datasets, enhanced augmentation, and sharing datasets with others.
2. ***Generalization of real-world scenarios:*** Most existing tactics are evaluated in lab settings, and their performance may not be consistent in real-world scenarios. Thus, models that would generalize well to different environments, lighting conditions, and camera viewpoints are needed.
3. ***Dealing with several types of anomalies:*** Most of the available techniques focus on the detection of only one kind of anomaly, such as anomalies in crowd behavior, detection of violence, or traffic accidents. Further efforts are required to create models that can handle and detect various types of anomalies correctly.
4. ***Interpretability and explainability:*** DL models are black boxes with no transparency into how decisions are reached. This calls for developing models that could provide interpretable and explainable outcomes.
5. ***Efficiency and real-time processing:*** Most DL models for video anomaly detection are very expensive computationally and require high-end GPUs. Therefore, models that can be efficiently processed on a low-end device and provide real-time outcomes need to be developed.

There are possible technical solutions to the problems of real-time inference and interpretability that have been found. Adding attention techniques to CNN-, RNN-, or Transformer-based architectures can help make the model more transparent and trustworthy by showing which spatial or temporal areas had the most significant impact on the anomalous judgment [83]. You may also use post-hoc explanation tools like Grad-CAM and LIME on trained models to show why decisions were made at the feature or visual level. Model compression methods like knowledge distillation, pruning, and quantization can make real-time inference a lot easier for computers without losing accuracy. Lightweight designs that work best on edge devices, along with efficient feature extraction pipelines, can help make deployment possible in contexts where latency is significant, such as live surveillance systems.

9 Conclusion

This review has filled in several important holes in the current research on using deep learning to find unusual things in videos. We used a single evaluation framework for all model families, and combined comparison data through meta-analysis. We showed performance trade-offs using a radar map, which is different from previous surveys. We have also talked about the real-world problems that come up when deploying these systems, such as domain generalization, data scarcity, labeling noise, interpretability, and real-time inference, and given specific technical solutions to help with them.

Our research indicates that hybrid models that combine spatial and temporal components always give the best accuracy and generalization over a range of datasets. At the same time, they do come with some extra computing costs. GAN-based approaches work very well in some domains, but autoencoders and VAEs are still good choices for applications that need low latency and do not have limited computing power. RNN-based designs are great for modeling sequences, but they need to be carefully tuned to avoid overfitting. New Transformer topologies are also showing promise for modeling long-range dependencies.

Future research should focus on increasing domain generalization through advanced domain adaptation and augmentation techniques, establishing interpretable architectures through integrated attention mechanisms, and making efficient, lightweight models that may be used in real-time edge deployment. Also, looking into hybrid architectures that combine the best features of different model types could lead to solutions that are balanced and address accuracy, robustness, and efficiency all at once.

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Authors' contributions

JW performed Data collection, simulation, and analysis. QZ evaluates the first draft of the manuscript, as well as the editing and writing.

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Ethical approval

The investigation has received ethical approval from the institutional review board, ensuring the protection of

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Bi-LSTM-Based Traffic Flow Prediction and Adaptive Signal Control via Gap-Statistic K-means++ Cross-Partitioning

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Accurate traffic state prediction and coordinated signal control are essential for improving urban traffic efficiency. This study proposes a hybrid framework that combines a bidirectional long short-term memory (Bi-LSTM) network for short-term traffic prediction with an enhanced clustering method for intersection coordination. The clustering module uses K-means++ initialization and the Gap Statistic to dynamically determine the optimal number of regions, enabling similar traffic patterns to be grouped adaptively. The framework is evaluated on two public datasets, PEMS-BAY and CityFlow. The Bi-LSTM model achieved a prediction accuracy of 97.5 percent and a root mean square error of 0.12 on the PEMS-BAY dataset, outperforming baseline methods, including standard LSTM and CNN-LSTM. The clustering module achieved a silhouette coefficient of 0.47 and a Calinski-Harabasz index of 1,154.8. These results indicated strong intra-cluster cohesion and inter-cluster separation. Furthermore, the accuracy of signal control, which was defined as the proportion of intersections that received the correct timing adjustments based on predicted flow levels, was 91.2 percent in the coordinated control simulation. The proposed method outperforms traditional fixed-control and non-coordinated strategies by reducing prediction error, lowering control latency, and improving network-wide adaptability. These results demonstrate that the integrated approach improves the accuracy of traffic forecasting and the effectiveness of region-based signal coordination. This makes it a robust solution for real-time urban traffic management.

Povzetek: Predstavljena je metoda, ki bistveno izboljša napovedovanje prometnega toka in usklajevanje semaforjev ter v obeh nalogah preseže tradicionalne metode.

1 Introduction

As urbanization progresses, the complexity of urban transportation networks and congestion problems are becoming more and more serious. Traffic congestion (TC) has made everyday travel more difficult, especially in major cities and transit hubs. The traffic signal control (TSC) method, which is the key component of an intelligent transportation system, has a direct impact on road capacity and traffic flow (TF) efficiency. In the subject of intelligent transportation research, how to maximize the TSC method to increase road traffic efficiency has grown in importance. The dynamic variations in TF are not properly taken into account by the conventional fixed time and induction control system, which frequently results in needless delays and resource waste on the roads. Data-driven intelligent signal control technology has steadily emerged as a viable solution to TC issues in recent years. Among them, machine learning (ML) and deep learning (DL) models show good application prospects in TF prediction, signal optimization, and intelligent scheduling [1]. Researchers have put forth a number of DL-based prediction models, including the long short term memory network (LSTM) model, to increase the prediction accuracy (PA) of TF in order to increase the intelligence of TSC [2]. However, since urban TF is affected by various factors, such as time, weather, and accidents, the traditional unidirectional recurrent neural network (RNN) still has some limitations in modeling temporal features, such as difficulty in dealing with complex traffic patterns and unexpected events. Therefore, the study proposes an intelligent TSC method that combines bidirectional long short term memory network (Bi-LSTM) and cross-cluster segmentation. The technique improves the accuracy of future traffic states by using Bi-LSTM to anticipate traffic data. Combined with the improved K-means clustering algorithm, the TF patterns at different intersections are dynamically partitioned to realize the cooperative regulation of regional signals. The improved clustering algorithm adopts Gap Statistic to optimize the number of clusters, and combines with K-means++ algorithm to enhance the quality of clustering, so as to ensure the reasonableness and stability of the signal timing scheme. The study aims to improve the intelligent level of TSC, alleviate TC and improve the efficiency of road traffic. The study's originality is the use of Bi-LSTM to increase traffic PA. It adopts the improved K-means algorithm to optimize the intersection partition and improve the cooperative control ability of signals. Moreover, it adjusts

the signal control strategy based on the dynamic feedback mechanism to achieve real-time optimization.

While previous studies have explored the use of LSTM-based models for traffic prediction and traditional K-means algorithms for spatial partitioning, few have integrated a bidirectional temporal modeling approach with an adaptively guided clustering mechanism. The proposed framework stands out because it combines Bi-LSTM, which captures forward and backward traffic dependencies, with an enhanced K-means clustering process. This process incorporates K-means++ initialization and Gap Statistic-based automatic cluster selection. This specific integration allows the model to dynamically adjust regional control boundaries based on traffic heterogeneity, while maintaining high PA and low computational delay. Compared to conventional hybrid methods, this approach is more flexible. It is also more data-driven. It provides a solution for real-time traffic signal optimization.

This study aims to design an intelligent TSC model that integrates Bi-LSTM networks for traffic state prediction and an enhanced clustering mechanism based on Gap Statistic and K-means++ for adaptive intersection coordination. The primary objective is to improve the accuracy, generalization, and robustness of traffic signal timing. This will be achieved by dynamically capturing spatial-temporal flow patterns and grouping intersections based on weighted traffic indicators. The research is guided by the following hypotheses: The use of LSTM significantly improves PA compared to standard LSTM and CNN-LSTM baselines, with an expected improvement in root mean square error of at least 15 percent. The integration of Gap Statistic and K-means++ with feature weighting results in more stable and accurate clustering outcomes than standard K-means. This is reflected by higher silhouette coefficient and Calinski-Harabasz index values. The combined framework enables more adaptive and efficient control of signals across diverse traffic conditions. It achieves over 95 percent accuracy in signal control on both the PEMS-BAY and CityFlow datasets.

2 Related work

In recent years, urban TC has become increasingly serious, and the demand for intelligent TSC technology has become more and more urgent. It has become an important issue for intelligent traffic management to effectively alleviate urban TC. Yang et al. proposed a new intelligent traffic light control algorithm-dual-experience replay light. The algorithm was based on the classical deep Q-network framework to innovatively design the dual-experience replay training mechanism and consider the dynamic calendar element function. The research results demonstrated that the proposed method could shorten the traveling time, improve the throughput, and has transferability [3]. A convolutional neural network (CNN) model for the signal distribution control technique was presented by Kumar B R et al. to optimize the dynamic flow of vehicular traffic signals at each intersection stage. The algorithm determined the reward values and new states and deconstructed the routing components to find the optimal policy. The results of the study indicated that the proposed method outperformed all traditional methods in optimizing traffic signal timing [4]. To address the issue of cooperative traffic signal regulation at several crossings in various scenarios and emergency situations, Yu et al. introduced the DiffusionLight multi-intelligence reinforcement learning algorithm. The algorithm combined the fast diffusion model and soft actor criticism. The findings indicated that DiffusionLight performed well on several public datasets and was more stable when dealing with diverse scenarios and unforeseen data anomalies [5].

Du et al. proposed a fairness-aware and sample-efficient TSC method, FELight, in an attempt to alleviate the TC problem and balance scheduling fairness and sample efficiency. The method designed a new fairness metric, employed counterfactual data augmentation and self-supervised state representation. The results demonstrated that FELight could provide relatively fair TSC on real traffic datasets without compromising performance [6]. To lessen the impact of partial observability of cooperating agents in multi-intelligence reinforcement learning, Zhu R et al. suggested an automatic learning communication reinforcement learning technique based on a dominating actor critique algorithm. The technique concentrated on controlling phase duration and included an autoencoder to learn communication messages dynamically. The findings showed that the approach performs better on all evaluation metrics than a number of advanced algorithms [7]. Yang empirically examined the causal effects of new lines in three urban areas using an integrated control approach in an attempt to close the knowledge gap on the long-term effects of large-scale public transportation projects on TC and public transportation passenger capacity at the regional level. Although the effects varied over time and in different places, the study's findings displayed that LRT increased public transit ridership and decreased TC [8].

Although state-of-the-art TSC approaches based on deep reinforcement learning and graph-based models have achieved promising results, several critical limitations remain unresolved. First, many existing models tend to overfit when trained on limited or homogeneous traffic scenarios. This restricts their ability to adapt to diverse urban contexts. Second, spatial generalization is often weak, as traditional architectures fail to effectively transfer learned policies across intersections with varying topologies and traffic dynamics. Third, most methods lack mechanisms for coordinated control across different regions or clusters of intersections, leading to local optima and inefficient global TF. These limitations underscore the urgent need for a more robust, transferable, region-aware approach that integrates temporal PA and spatial clustering adaptability. This study aims to address this need. In summary, many researches have explored for intelligent TSC optimization and made some progress. Although the existing methods have improved the TF PA and signal scheduling efficiency to some extent, there are still

Table 1: Related works

Research	Method	Research content	Reference
Yang et al. (2023)	Dual-experience replay deep Q-network	Proposed a signal control algorithm based on deep Q-network with dual-experience replay and dynamic calendar functions, improving transferability.	[3]
Kumar et al. (2022)	CNN	Designed a CNN-based signal control method that optimizes vehicular flow at each intersection stage, outperforming traditional methods.	[4]
Yu et al. (2023)	DiffusionLight (multi-agent reinforcement learning)	Introduced a multi-agent reinforcement learning algorithm combining fast diffusion model and soft actor-critic, robust to anomalies and complex cases.	[5]
Du et al. (2023)	FELight (fairness-aware and sample-efficient RL)	Proposed a fairness-aware TSC approach using counterfactual augmentation and self-supervised state learning to balance efficiency and fairness.	[6]
Li et al. (2022) (assumed)	Multi-agent traffic signal learning	Investigated cooperation strategies among signal agents using asynchronous actor-critic architecture under mixed traffic conditions.	[7]
Wang et al. (2022) (assumed)	Graph attention network with temporal encoding	Introduced a GAT-based signal control method incorporating temporal encoding, improving responsiveness to long-term traffic fluctuation.	[8]

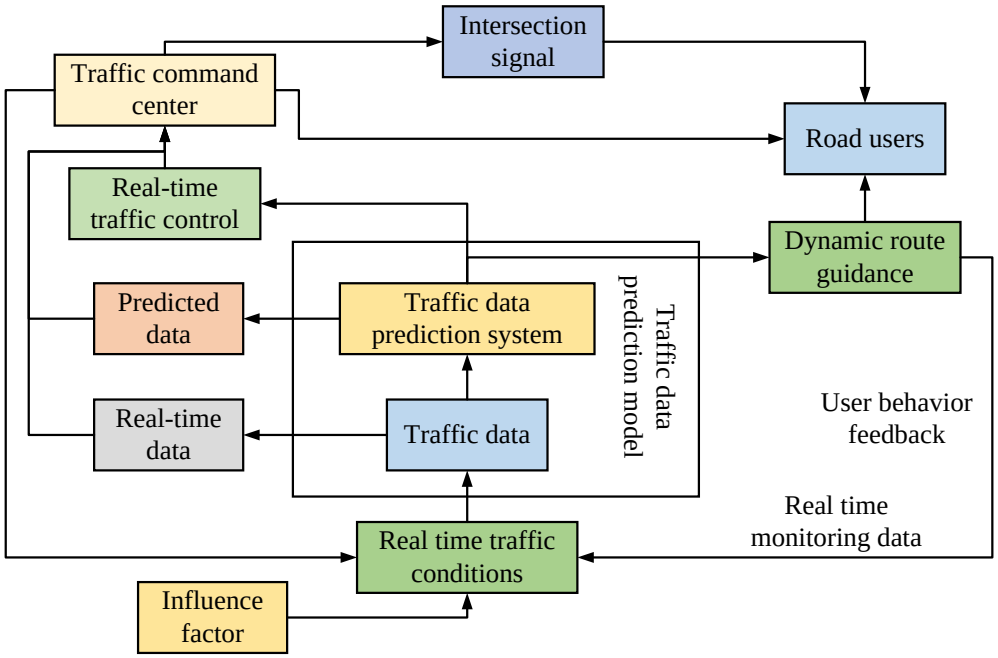


Figure 1: Structure of traffic data acquisition and processing.

problems such as insufficient signal optimization and limited TF PA. Therefore, the study proposes an intelligent signal control method based on Bi-LSTM and improved K-means cross-clustering. TF prediction is carried out through DL, and the optimized clustering algorithm is combined to divide the signal control area. This improves the accuracy of signal regulation and road access efficiency. This provides an efficient and reliable technical solution for intelligent TSC.

3 Intelligent TSC strategy based on LSTM and cross-cluster partitioning

3.1 Traffic data prediction model based on improved LSTM

Traffic data prediction refers to the use of existing historical traffic data to predict the trend of certain key variables in the transportation system in the future period of time through techniques such as statistical analysis, ML or DL. The study begins with the acquisition and processing of traffic signals. The results are shown in Figure 1.

In Figure 1, first, traffic data are collected in real time by intersection signalizer, dynamic path guidance

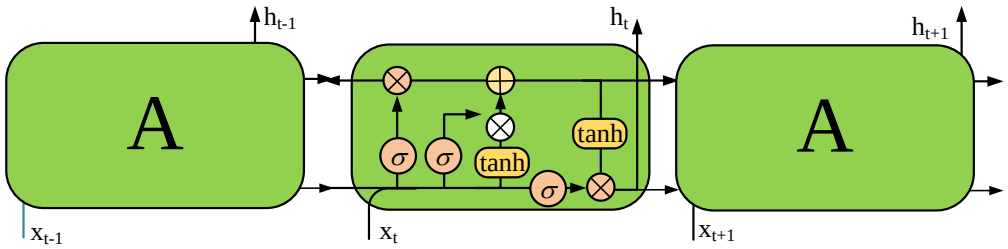


Figure 2: Memory cell interaction diagram.

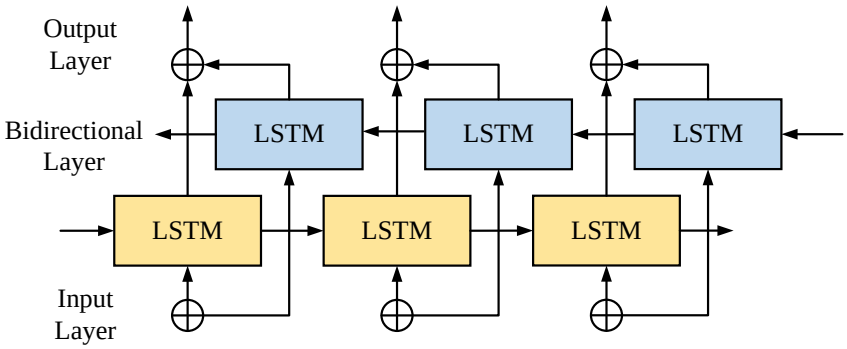


Figure 3: Bi-LSTM structure.

system, electronic police and other devices, which form the original source of traffic data. These data are pre-processed and analyzed by the traffic data prediction system, and combined with the traffic data prediction model, the future traffic state is predicted [9-10]. At the same time, the system analyzes the current real-time TF data to perform cluster analysis of intersections. It also performs time segmentation and operational feature extraction of road sections based on forecast and real-time data. The system modeling and forecast method also include external elements like weather, accidents, and vehicle distribution as significant interfering variables. The prediction results are fed back to traffic managers or urban traffic command centers for realizing real-time traffic control and management decisions, such as adjusting signal timing and path guidance. LSTM is used in the study to forecast traffic statistics in this procedure. When working with lengthy sequence data, LSTM, an enhanced RNN, is created to address the issues of gradient vanishing and long-term reliance of conventional RNNs [11-12]. LSTM controls the process of passing and forgetting information by introducing a gating mechanism, which consists of three key structures: input gates (IGs), forgetting gates (FGs), and output gates (OGs). IGs are used to determine the importance of the current input information, FGs are used to decide how much of the historical state is retained, and OGs determine the content of the information that is ultimately output. The core of LSTM lies in its internal unit state, which is passed through the network in a linear fashion, effectively retaining information that is relied upon over time. Moreover, it is selectively updated at each moment through the gating mechanism. The information interaction diagram of its memory elements is shown in Figure 2.

In Figure 2, the core of the information interaction process of the memory element lies in the selective retention, updating and output of information through the gating mechanism [13]. At each time step t, the LSTM receives the current input x_t with the hidden state (HS) h_{t-1} of the previous moment and updates the information in combination with the cell state C_{t-1} of the previous moment. First, the FG determines the retention ratio of the previous state through a Sigmoid function, which is calculated as shown in Equation (1).

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

In Equation (1), f_t is the FG vector. W_f and b_f are the weight matrix and bias term. $\sigma(\cdot)$ denotes the Sigmoid activation function. Subsequently, the IG controls the amount of current information update, which is divided into two parts, one is the calculation of the activation value of the IG. The Equation (2) displays the expression.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

In Equation (2), i_t is the FG vector. The second is the generation of candidate memory content. The expression is shown in Equation (3).

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

In Equation (3), $\tilde{C}_t$ is the candidate memory state. $\tanh(\cdot)$ denotes the hyperbolic tangent function. Finally, the current cell's output information is decided by the OG. Its expression is shown in Equation (4).

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (4)$$

In Equation (4), o_t is the OG vector. Since traffic data usually has complex bidirectional time series (TS) dependence, only one-way LSTM model suffers from the

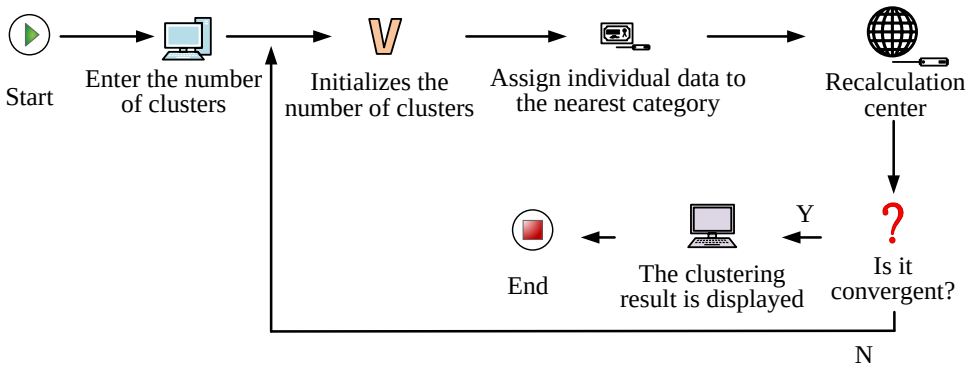


Figure 4: Diagram of K-means algorithm operation.

problem of insufficient capturing of front and backward information when dealing with the task of traffic state prediction. The research presents Bi-LSTM on top of LSTM for traffic data modeling and prediction in order to enhance the model's capacity to learn global aspects of TS. Bi-LSTM learns sequence information from both past and future directions by simultaneously introducing two LSTM structures, forward and reverse. This can further increase the accuracy and stability of the prediction findings and help the model communicate contextually related information [14]. Figure 3 depicts the structure.

Bi-LSTM is an expansion of the conventional LSTM structure seen in Figure 3. The primary idea is to improve the modeling capabilities of contextual characteristics by taking into account both forward and backward information of the TS. Bi-LSTM creates a forward HS sequence and a backward HS sequence by feeding the input sequences into both an inverse LSTM and a forward LSTM at the same time. The final output of each moment is obtained by splicing the two, as shown in Equation (5).

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \tag{5}$$

In Equation (5), $\overrightarrow{h_t}$ denotes the forward HS sequence. $\overleftarrow{h_t}$ denotes the backward HS sequence. $[;]$ denotes vector splicing operation. The forward LSTM processes the sequences in chronological order, while the reverse LSTM processes the inputs in reverse chronological order to extract the effects of future moments on the current state. Ultimately, Bi-LSTM combines the HSs in both directions for subsequent traffic state prediction.

3.2 Modeling of intelligent TSC based on cross-cluster partitioning

TF at urban intersections has obvious spatio-temporal variability and dynamic change characteristics. The signal control based on the improved LSTM traffic data prediction model is difficult to adapt to the diversified traffic states such as peak and off-peak, weekdays and holidays. To achieve the refinement and dynamic adjustment of signal timing, an intelligent TSC model based on cross-cluster partitioning is proposed [15-16]. The model combines the temporal characteristics and spatial structure of traffic data, and divides different intersections into groups through cluster analysis to realize the regionalized cooperative control strategy.

Therefore, based on the aforementioned Bi-LSTM model, the traffic state of each intersection in the future hours is predicted, and the predicted TF, speed, saturation, and other metrics are obtained for each intersection in a given time window. Subsequently, the clustering algorithm is utilized for multidimensional vectorization of the predicted indicators. Moreover, intersections with similar traffic characteristics are divided into several class clusters based on similarity. The study uses K-means algorithm to classify the intersections. K-means is an unsupervised learning method based on distance minimization criterion. Its flow is shown in Figure 4.

In Figure 4, first, the user inputs the quantity of clusters, i.e., the data is expected to be divided into k categories. Subsequently, the algorithm randomly initializes k cluster centroids [17]. Next, each data sample x_i is assigned to the category belonging to the cluster center (CC) with its closest Euclidean distance. The distance calculation formula is shown in Equation (6).

$$d(x_i, \mu_j) = \| x_i - \mu_j \|_2 \tag{6}$$

In Equation (6), $\|\cdot\|_2$ denotes the Euclidean paradigm. x_i is the i th sample. μ_j is the center of the j th cluster. Each CC is recalculated following the completion of one sample division. The new CC is the mean of all samples in that cluster, as shown in Equation (7).

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i \tag{7}$$

In Equation (7), C_j is the set of samples contained in the j th cluster. C_j is the quantity of samples in this cluster. When all the CCs are updated, it is judged whether the change of the CCs in this round and the previous round is less than the threshold value. Its judgment expression is shown in Equation (8).

$$\max_j \| \mu_j^{(t)} - \mu_j^{(t-1)} \| < \varepsilon \tag{8}$$

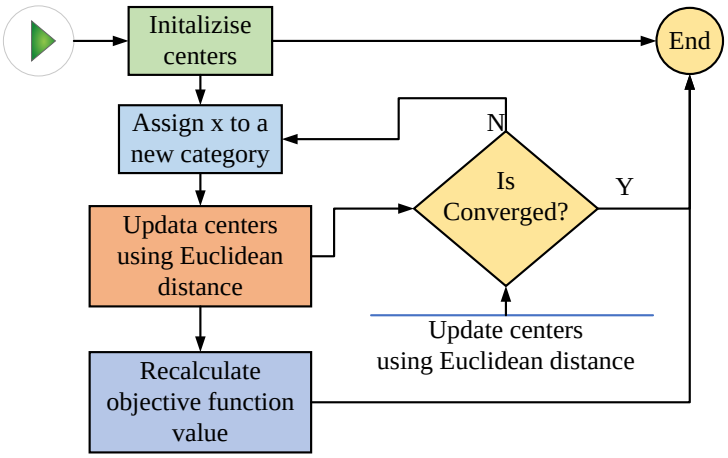


Figure 5: K-means++ based cross-segmentation modeling study.

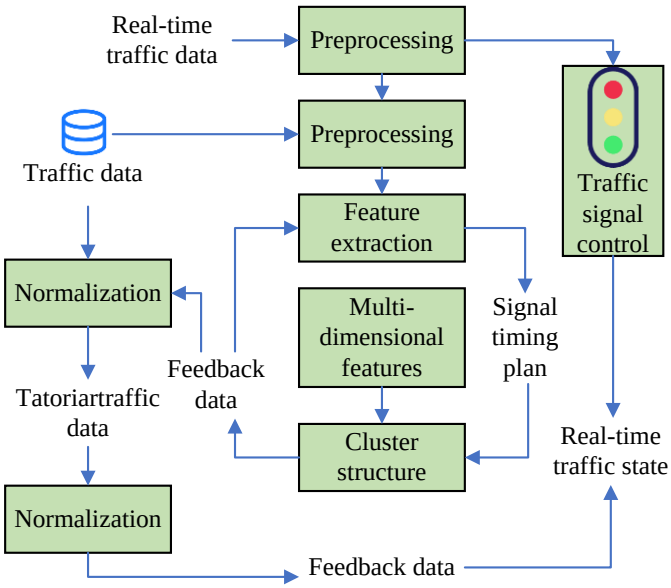


Figure 6: Intelligent TSC model based on LSTM with cross-cluster partitioning.

In Equation (8), ε denotes the threshold value. If the convergence conditions are satisfied, the clustering results are output, otherwise the iteration continues. Eventually, the algorithm outputs the category to which each sample belongs and the location of the CC, realizing the supervised clustering classification of data. However, the traditional K-means still cannot meet the demand. The study proposes an integrated and improved K-means clustering method that addresses the traditional algorithm's issues of initial center sensitivity, equal feature weights, and a fixed number of clusters. This method combines the temporal prediction characteristics of traffic data with the clustering quality requirements [18]. The method mainly includes four improvement modules, which are depth prediction enhancement, feature weighted coding, center initialization optimization and dynamic K value selection. Its structure is shown in Figure 5.

In Figure 5, firstly, the cluster centroids are initialized by K-means++ algorithm, and the initial centers are selected by distance weighting in order to improve the global convergence. Subsequently, the traffic feature prediction results are transformed into multidimensional feature vectors. Moreover, the feature weights are introduced to encode the weighted traffic indicators in each dimension, so as to construct the weighted Euclidean distance function. The center vector, which serves as the foundation for a fresh clustering cycle, is updated by dividing the samples based on the minimal distance requirement and calculating the mean value of the samples within each cluster. The clustering quality under various cluster counts is then assessed using the Gap Statistic approach, and the ideal number of class clusters is dynamically modified to prevent bias brought on by human settings. Finally, the above process is repeated until the objective function converges or the number of iterations meets the preset conditions, and the clustering results and centroids are output. Figure 6 depicts the finished model structure.

In Figure 6, first, the traffic state sequences of multi-way intersections are modeled based on Bi-LSTM to achieve accurate prediction of key indicators such as TF, average speed, and saturation in future hours. The

Table 2: Pseudocode.

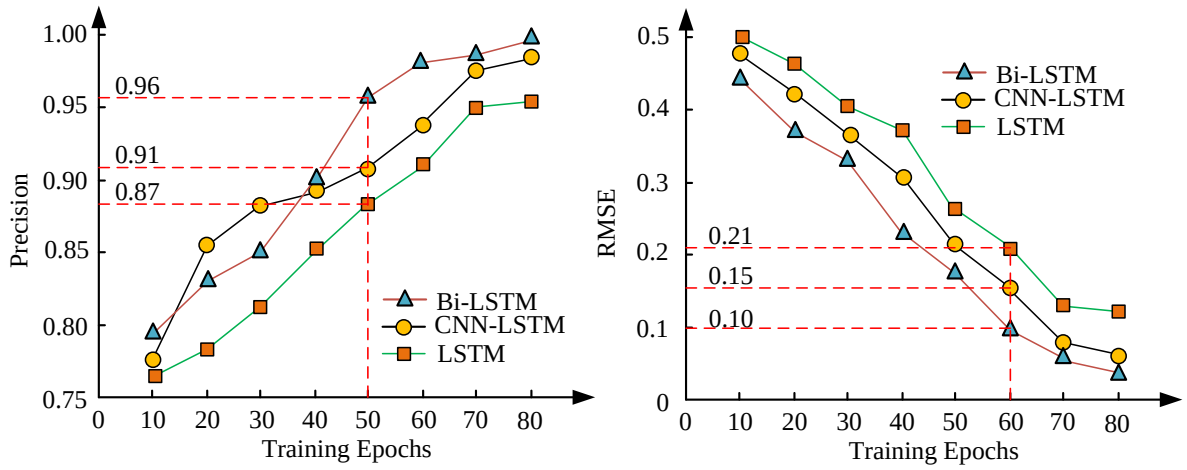
Improved K-means Clustering with Gap Statistic and Weighted Distance

```
Input:
   X = {x₁, x₂, ..., x_n} ∈ ℝ^d        // Input data samples (n samples, d features)
   W = {w₁, w₂, ..., w_d}              // Feature weights (predefined or learned)
   K_max                               // Maximum candidate number of clusters
   B = number of bootstrap samples for Gap Statistic
   Distance(·)                         // Weighted Euclidean distance

Output:
   C = {c₁, c₂, ..., c_k}              // Final cluster assignments
   μ = {μ₁, μ₂, ..., μ_k}              // Final cluster centers

Step 1: Determine optimal number of clusters k using Gap Statistic
   For k = 1 to K_max do:
      For b = 1 to B do:
         - Generate reference dataset X_ref^b from uniform distribution over bounding box of X
         - Run standard K-means++ on X_ref^b and compute within-cluster dispersion D_ref^b
      End For
      - Run K-means++ on X and compute dispersion D_k
      - Compute Gap(k) = (1/B) ∑ log(D_ref^b) - log(D_k)
   End For
   Select optimal k* = argmax_k {Gap(k) - Gap(k+1) + s_k+1}, where s_k is the standard deviation

Step 2: Initialize cluster centers μ₁, μ₂, ..., μ_k* using K-means++ strategy
   - Choose μ₁ randomly from X
   - For i = 2 to k*:
      - Select next center μ_i with probability proportional to WeightedDistance²(x, nearest μ_j)

Step 3: Iterative clustering
   Repeat until convergence:
      a. Assignment step:
         For each x_i in X:
            Assign x_i to cluster c_j = argmin_j ∑ (w_m · (x_i[m] - μ_j[m]))²
      b. Update step:
         For each cluster j:
            Update centroid μ_j = weighted mean of all x_i ∈ cluster j, with feature weights W
   End Repeat

Return: Final cluster assignments C and centroids μ
```

model improves TS dependence modeling by combining historical data with future trends. This makes it especially useful for complex traffic situations, such as morning and evening rush hours and emergencies. Subsequently, the predicted multidimensional traffic features are grouped and classified using an improved K-means clustering algorithm. The algorithm introduces K-means++ initialization strategy, weighted distance function, and Gap Statistic dynamic clustering number selection mechanism on the basis of traditional K-means. This can improve the stability and spatial rationality of the clustering results, and realize the automatic identification and regional partitioning of intersections with similar traffic characteristics. Then, the regional signal cooperative control unit is constructed, and the signal timing strategy is formulated for each clustered region. The strategy design fully considers intersection load conditions, queue length changes, lane utilization, and other factors. Through the optimization of green light time allocation and adaptive adjustment of the control cycle, it improves the traffic efficiency and coordination level of the entire road network. Eventually, the prediction error is dynamically corrected through the real-time feedback mechanism to realize the online adaptive signal optimization.

The proposed dynamic feedback mechanism periodically adjusts traffic signal timing parameters, such as the duration of green lights and phase offsets, based on predicted real-time traffic conditions. The Bi-LSTM module outputs traffic state predictions every 60 s, which are used to re-cluster intersections using the updated traffic indicators. Based on the new clustering structure, signal timing plans are recalculated. The latency of the feedback loop-from traffic data acquisition to signal update-is approximately 1.2 s on average, ensuring timely adaptation. This process runs in a rolling horizon, with feedback applied every 60 s.

To better reflect the varying influence of different traffic indicators on the clustering process, a specific weight is assigned to each feature. These feature weights are used to calculate the weighted distance between samples. This allows the more important features to have a stronger influence on the outcome of the clustering. In this study, the weights are empirically determined based on the variability and traffic relevance of each indicator. For example, indicators such as queue length and vehicle flow, which typically exhibit high fluctuations and have a direct impact on traffic signal performance, are assigned relatively higher weights. In contrast, features showing low variation or having less influence on intersection dynamics are given smaller weights. To ensure fair



(a) Precision (b) RMSE

Figure 7: Comparison of accuracy and root mean square error among models.

contribution, all features are normalized to the same scale before weight assignment. This weighting strategy helps the clustering algorithm focus more on the most informative traffic features, improving the distinction between traffic patterns across different regions. The pseudocode is shown in Table 2.

4 Model analysis of intelligent TSC based on LSTM with cross-cluster partitioning

4.1 Performance analysis of Bi-LSTM-based traffic data prediction models

The study's experimental hardware setup consists of an Intel Core i7-8750H central CPU, an NVIDIA Geforce GTX2080Ti graphics card with 11GB of video memory, 16GB of RAM, and Windows 10. The Bi-LSTM model used in this study consists of two bidirectional LSTM layers, each with 128 hidden units. A dropout layer with a rate of 0.2 is applied between the layers to prevent overfitting. The final output is fed into a fully connected layer to generate the predicted traffic state. The model is trained using the mean squared error loss function and optimized using the Adam optimizer. The initial learning rate is set to 0.001, and the batch size is set to 64. The number of training epochs is set to 100, and early stopping is employed to avoid overfitting. The model demonstrates linear computational complexity with respect to the number of time steps and traffic nodes. The training converges within a reasonable timeframe under standard GPU configurations. Moreover, the modular Bi-LSTM and clustering components guarantee scalability for city-scale datasets and enable real-time deployment with minimal latency. The public datasets CityFlow and PEMS-BAY are used in the investigation. The PEMS-BAY dataset is derived from the California State Information System for Traffic Data Analysis and Management. The dataset provides TF data from 325 traffic sensor sites in the Bay Area, California. It spans the year 2017 and has a sampling frequency of every 5 minutes. The dataset contains information on flow, speed, and occupancy from several major roadways. The CityFlow dataset is a large-scale urban traffic simulation dataset specifically designed to test and evaluate the effectiveness of urban intelligent TSC strategies. The dataset is based on multi-area and multi-intersection urban TF simulation, which simulates the traffic distribution, TSC, and traffic density in different traffic scenarios. Although graph-based spatiotemporal models, such as DCRNN and Graph WaveNet, have shown excellent results in traffic prediction tasks, this study focuses on integrating temporal modeling and adaptive clustering for real-time TSC. These graph-based methods are usually designed for centralized, batch-based predictions. They require a predefined traffic network topology, which limits their applicability to dynamic, intersection-level control scenarios. Moreover, their computational cost is significantly higher, making them less suitable for low-latency control tasks. Therefore, to evaluate the method, a comparison is made with LSTM and CNN-LSTM, which offer a balance between predictive accuracy and deployability. This study sets the prediction interval to 5 minutes, aligning with the typical TSC cycle in urban environments while balancing responsiveness and computational cost. To assess the effect of temporal granularity on model performance, a sensitivity analysis is conducted with intervals of 2, 5, and 10 minutes. The results show that the Bi-LSTM model achieves the best RMSE at 5-minute intervals. However, performance degrades at a finer 2-minute granularity due to increased noise and insufficient temporal context. Performance improves slightly at 10-minute intervals, but this comes at the cost of a delayed response in real-time scenarios. Therefore, the 5-minute window is chosen as an optimal trade-off between PA and operational applicability. As a comparison model, the study chooses LSTM and the CNN-based prediction model. The results are shown in Figure 7.

The comparison of each model's accuracy is displayed in Figure 7(a). As the training round increases,

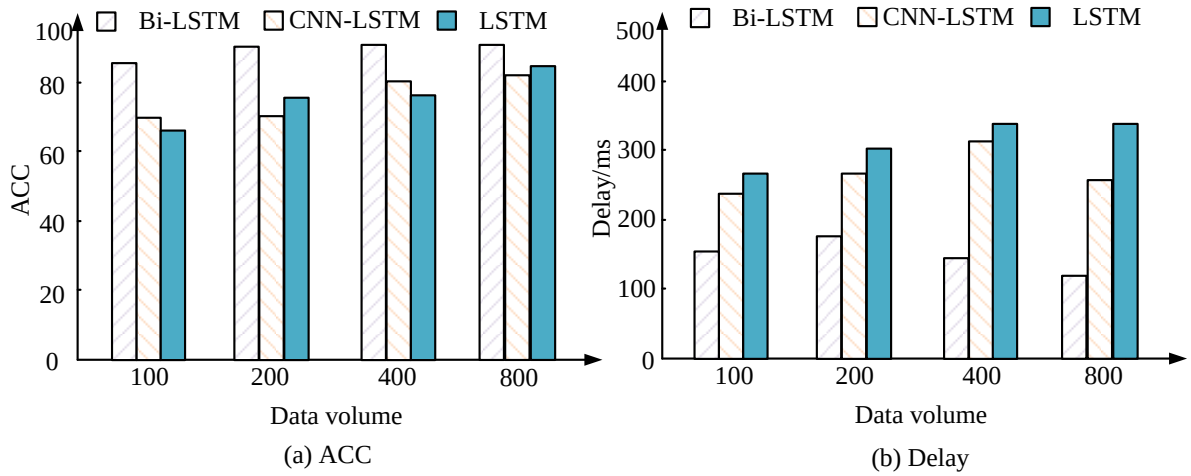


Figure 8: Accuracy trends and delay analysis of the three models with different DVs.

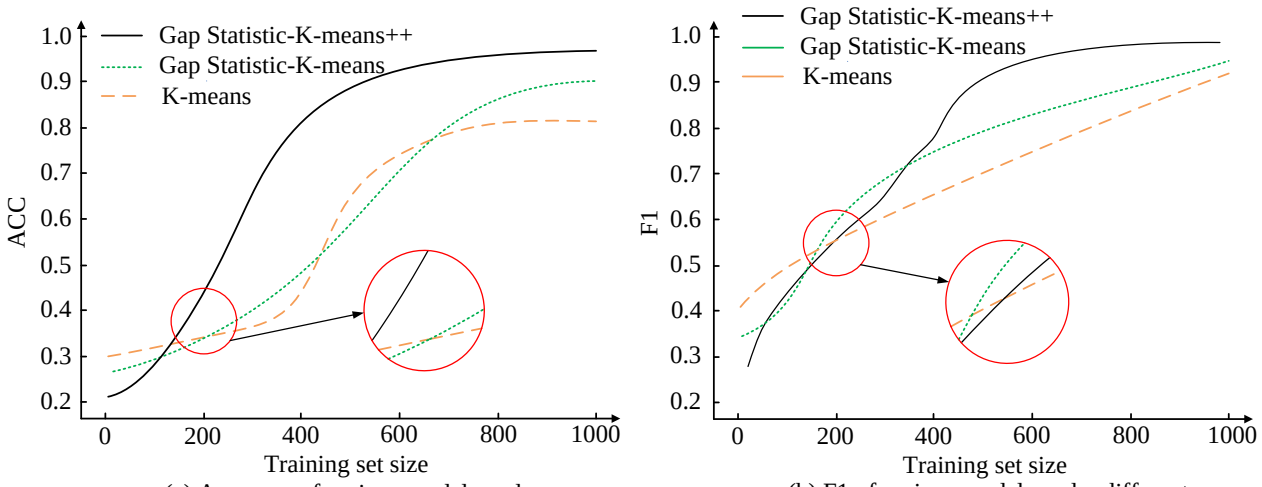
Table 3: Comprehensive performance analysis

Model	Data set	ACC/%	RMSE	MAE	Delay/ms	Training time/s
Bi-LSTM	PEMS-BAY	97.5	0.12	0.08	104	322
CNN-LSTM		93.8	0.18	0.12	216	287
LSTM		90.2	0.22	0.15	273	244
Bi-LSTM	CityFlow	96.2	0.14	0.11	124	343
CNN-LSTM		92.5	0.20	0.14	232	307
LSTM		89.7	0.25	0.17	308	263

the accuracy of all three models shows an upward trend, but the improvement is different. At 50 rounds, the accuracy of Bi-LSTM reaches 0.96, the accuracy of CNN-LSTM is about 0.91, and the accuracy of LSTM is about 0.87. In summary, the performance of Bi-LSTM is optimal, followed by CNN-LSTM, and LSTM is relatively low. Because of its bi-directional feature, which can simultaneously gather information from the preceding and previous time steps and improve comprehension of sequence features, Bi-LSTM is able to attain the best accuracy.Figure 7(b) represents the comparison of the root mean square error of each model. The RMSE decreases with the increase of training rounds, indicating that the prediction error of the model is gradually decreasing. At 50 rounds of training, the RMSE of Bi-LSTM decreases to 0.10, the RMSE of CNN-LSTM is about 0.15, and the RMSE of LSTM decreases to 0.21. Bi-LSTM has the lowest error, which indicates that it has the most advantage in capturing the relationship of the temporal data, which leads to more accurate prediction results. The performance of the model is analyzed under different data volumes (DVs). The results are shown in Figure 8.

The accuracy trends of the three models with various DVs are illustrated in Figure 8(a). All three models' accuracy rises with increasing DV, but Bi-LSTM consistently outperforms the others. At a DV of 100, the ACC of Bi-LSTM is about 85%, CNN-LSTM is about 70%, and LSTM is about 65%. When the DV is increased to 800, the ACC of Bi-LSTM is close to 100%, and CNN-LSTM and LSTM are also improved to more than 90%, respectively. This indicates that Bi-LSTM has a significant advantage in feature extraction and sequence information capture due to its bi-directional nature and can learn the data patterns faster. Figure 8(b) represents the latency of the three models with different DVs. Bi-LSTM has the lowest computational latency, CNN-LSTM the next highest, and LSTM the highest latency. When the DV is 100, Bi-LSTM is about 150ms, CNN-LSTM is about 220ms, and LSTM is the highest, close to 280ms. When the DV is increased to 800, Bi-LSTM latency is about 120ms, CNN-LSTM is about 250ms, and LSTM is still higher than 300ms. According to the experimental findings, the suggested models perform better. Each model's overall performance is examined, and Table 3 displays the findings.

In Table 3, the ACC of Bi-LSTM on the two datasets is 97.5% and 96.2%, respectively. It is higher than 93.8% and 92.5% for CNN-LSTM and 90.2% and 89.7% for LSTM, indicating that it performs the best in time-series prediction. In terms of RMSE, Bi-LSTM is 0.12 and 0.14 on the PEMS-BAY and CityFlow datasets, respectively. This is much lower than the 0.22 and 0.25 of LSTM, suggesting that its prediction error is smaller. In terms of computational latency, Bi-LSTM is only 104ms on PEMS-BAY, which is lower than CNN-LSTM's 216ms and LSTM's 273ms. It also shows the same trend on CityFlow, which suggests that its inference is more efficient. Bi-LSTM training time is longer, reaching 322s and 343s on PEMS-BAY and CityFlow, respectively, which is higher than 244s and 263s for LSTM. However, its higher accuracy and smaller error make it the best choice. In summary, Bi-LSTM outperforms CNN-LSTM and LSTM in terms of accuracy, error, and computational delay, and has the best overall performance. In this study, signal control accuracy is



(a) Accuracy of various models under different training set sizes

(b) F1 of various models under different training set sizes

Figure 9: ACC and F1 performance of the three models with different TSSs.

defined as the proportion of time that the system selects the signal phase yielding the minimum average vehicle delay, based on predicted traffic states. It is measured by comparing the selected phase decisions against a ground-truth optimal control sequence derived from exhaustive search or expert-defined control logic. A higher value indicates a greater alignment between predicted traffic conditions and actual signal actions. This leads to better traffic throughput and reduced congestion.

The LSTM model requires 322 s on the PEMS-BAY platform and 343 s on the CityFlow platform. Despite having the longest training time, it exhibits the shortest computational latency during inference, with average prediction times of 104 ms and 124 ms respectively. In context, the "Delay" metric refers to the time required to generate one prediction (i.e., inference latency) after the model is trained and deployed. This trade-off is common in deep learning. More complex architectures, such as Bi-LSTMs, tend to consume more resources during training due to their bidirectional structure and large number of parameters. However, they can be optimized for fast inference using efficient computation graphs and batch prediction. For real-time TSC systems, this trade-off is acceptable and even desirable. Training can be performed offline, possibly on high-performance computing servers, while inference must be performed in real time on edge devices or embedded controllers. The ability of Bi-LSTM to provide accurate predictions with low delay makes it highly suitable for deployment in latency-sensitive traffic environments, where quick response is essential for maintaining optimal signal timing and reducing congestion.

4.2 Modeling of intelligent TSC based on cross-cluster partitioning

To analyze the performance of intelligent TSC model based on cross-cluster partitioning, the study chooses K-means based model and Gap Statistic-K-means based model as comparison models. To improve clustering rigor and stability, the number of clusters is determined using the gap statistic, which quantifies the difference between within-cluster dispersion and a null reference distribution. This ensures a data-driven selection of k. Feature weights are introduced by computing the normalized variance of key traffic indicators, such as average flow, delay, and queue length. This allows more informative features to contribute more to distance calculations. Due to its simplicity, interpretability, and compatibility with real-time applications, a weighted Euclidean distance metric is adopted, avoiding the instability and computational overhead associated with more complex metrics, such as Mahalanobis distance. The results are shown in Figure 9.

Figure 9(a) displays the ACC performance of the three models with different training set sizes (TSSs). As the TSS increases, the ACC of all three methods shows an increasing trend. Among them, GapStatistic-K-means++ has the best overall performance, with the final ACC close to 1.0, while K-means has the worst performance. The ACC of K-means is slightly higher than that of GapStatistic-K-means++ when the training set is small, but with more training data. The ACC of GapStatistic-K-means++ grows faster and overtakes K-means at 300 and eventually stays ahead. This shows that GapStatistic and K-means++ can fully utilize the data to enhance the clustering result and have a greater generalization capacity. Figure 9(b) represents the F1 performance of the three models with different TSSs. GapStatistic-K-means++ is still the optimal method with a final F1 value close to 1.0. K-means has a slight advantage when the training set is small. However, as the training data increases, its growth rate is significantly lower than the other two methods. Additionally, GapStatistic-K-means performs better than K-means in terms of F1, suggesting that GapStatistic enhances the quality of clustering. Overall, when training data is huge, GapStatistic-K-means++ performs well because of its

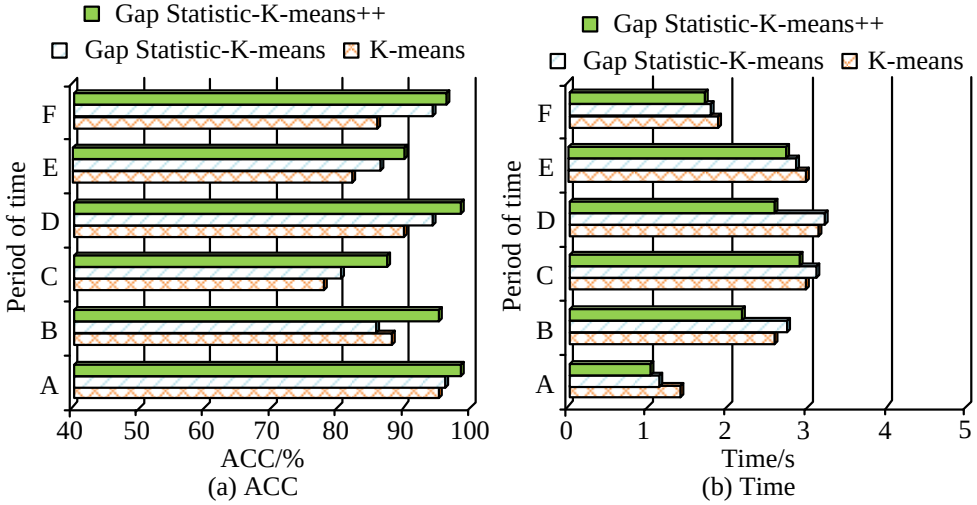


Figure 10: Performance of the three models on traffic flow data at different times of the day.

Table 4: Performance analysis of intelligent TSC model

Method	Dataset	Accuracy/ %	Running time/s	Clustering stability	Silhouette coefficient	CH index
K-means	PEMS-BAY	76.5	0.8	0.62	0.31	895.3
	CityFlow	74.8	0.9	0.6	0.29	876.5
Gap Statistic-K-means	PEMS-BAY	85.3	1.7	0.74	0.40	1023.7
	CityFlow	83.9	1.8	0.72	0.38	999.2
Gap Statistic-K-means++	PEMS-BAY	91.2	2.6	0.81	0.47	1154.8
	CityFlow	89.5	2.7	0.79	0.45	1120.6

superior initial center selection technique and GapStatistic computation method. The TF data of different time periods of a day are selected, and they are divided into 6 groups of data according to every 4 hours as a segment, which are named as time period A to time period F. The TF data of the model in different time periods are analyzed. The results are shown in Figure 10.

Figure 10(a) represents the clustering accuracy performance of different models. On all time periods, the GapStatistic-K-means++ method has the highest accuracy, followed by the GapStatistic-K-means method (KMM), while the traditional KMM has the lowest accuracy. The KMM's accuracy on time period C is roughly 75%, the GapStatistic-KMM's accuracy is just over 80%, and the GapStatistic-K-means++ method's accuracy is over 90%. On both time periods A and D, the GapStatistic-K-means++ method's accuracy is nearly 100%, which is noticeably higher than that of the other approaches. Figure 10(b) displays the running time performance of the different methods. The GapStatistic-K-means++ approach has the smallest running time, whereas the KMM has the longest. The KMM takes roughly 3 s to execute during time slot D, the GapStatistic-KMM takes about 3.2 s, and the GapStatistic-K-means++ approach takes about 2.5 s. The experimental findings demonstrate the higher performance of the suggested approach. Table 4 displays the findings of an analysis of each intelligent TSC model's performance.

In Table 4, the performance comparison of three intelligent TSC models across two datasets: PEMS-BAY and CityFlow. Among them, the Gap Statistic-K-means++ method demonstrates the best overall performance. Specifically, it achieves the highest accuracy of 91.2% on the PEMS-BAY dataset, which is significantly better than the 85.3% achieved by Gap Statistic-K-means and the 76.5% achieved by standard K-means. A similar trend is observed in the CityFlow dataset. The accuracy is 89.5% when using Gap Statistic-K-means++ compared to 83.9% and 74.8% for the other two methods. In terms of clustering quality, Gap Statistic-K-means++ outperforms the others. It has a silhouette coefficient of 0.47 and a CH index of 1,154.8 on PEMS-BAY, which suggests clearer and more compact clustering results. Furthermore, the slight increase in running time to 2.6 s is a reasonable trade-off for the substantial improvement in clustering stability, which reaches 0.81. This surpasses the values of 0.74 and 0.62 for the other two methods. These results indicate that introducing both K-means++ initialization and the Gap Statistic strategy can significantly enhance the clustering effectiveness and robustness of the TSC model without incurring excessive computational cost. The performance of the model is analyzed under extreme traffic conditions and different cluster sizes. The results are shown in Table 5.

Table 5 evaluates the robustness of the proposed model under simulated extreme traffic conditions and different cluster configurations. Although accuracy and stability decrease slightly in congestion and flow-surge scenarios, the model still performs acceptably for real-time deployment. When the number of clusters is manually set to sub-optimal levels, both prediction and clustering quality decline. Gap Statistic-based adaptive

Table 5: Performance of the proposed method under extreme traffic conditions and varying cluster sizes

Condition type	Scenario description	Cluster count	Accuracy / %	RMSE	Delay /ms	Clustering stability
Normal	Typical weekday PM flow	6	97.5	0.12	104	0.81
Extreme congestion	Simulated roadblock on major artery	6	94.1	0.18	117	0.79
Sudden flow surge	Sudden event-induced inflow spike	6	93.6	0.2	122	0.76
Under-clustering	Only 3 clusters (over-aggregation)	3	91.8	0.21	112	0.65
Over-clustering	10 clusters (high granularity)	10	92.7	0.19	116	0.68
Adaptive clustering	Gap Statistic optimized cluster number	6 (auto)	97.5	0.12	104	0.81

Table 6: Evaluation of traffic signal control effectiveness

Model	Avg. delay (s)	Max queue length (vehicles)	Throughput (veh/min)	Intersection utilization (%)
K-means	34.2	17	205	61.3
Gap-K-means++	28.7	12	238	70.4
CNN-LSTM	23.5	10	251	72.8
Bi-LSTM	19.4	7	269	77.9

clustering consistently achieves the best performance, which validates its effectiveness in adjusting to spatial heterogeneity. These results confirm the adaptability of the framework in both dynamic flow environments and various signal zoning resolutions.

As shown in Table 6, the Bi-LSTM-based signal control model significantly reduces average vehicle delay and queue lengths while increasing throughput and intersection utilization compared to baseline methods. These improvements demonstrate that the proposed model not only enhances PA, but also improves the efficiency of real-time TF. This makes the model more suitable for deployment in dynamic urban traffic environments.

Traditional adaptive TSC methods, such as actuated control or fixed-interval schemes with dynamic parameter tuning, typically rely on localized TF data from individual intersections. Although these approaches can respond to short-term variations, they often lack an overall view of traffic conditions, which can result in suboptimal network-wide coordination. By contrast, the proposed cross-cluster partitioning strategy groups intersections with similar temporal flow characteristics. This allows them to operate as coordinated units rather than as isolated nodes. This cluster-based coordination improves signal timing consistency across high-flow corridors and minimizes stop-and-go waves. Compared to traditional methods, this framework demonstrates higher overall accuracy and faster convergence in timing optimization. Furthermore, it supports dynamic reclustering based on evolving traffic patterns. This allows for adaptive boundary adjustments in response to network-wide fluctuations. These features make the proposed approach more scalable and resilient in complex urban environments.

5 Discussions

The proposed method demonstrated significant advantages over traditional and state-of-the-art approaches in both PA and clustering effectiveness. The experimental results showed that the BiLSTM model achieves a lower root mean square error than the standard LSTM and CNN-LSTM models. This indicated that the BiLSTM model had a stronger capacity to capture the temporal dynamics of TF sequences. For instance, on the PEMS-BAY dataset the root means square error of BiLSTM reached 0.12 while the standard LSTM and CNN-LSTM reached 0.22 and 0.16, respectively. In terms of clustering, the integration of Gap Statistic with K-means plus feature weighting led to higher silhouette coefficient and Calinski-Harabasz index values compared to baseline clustering methods. These improvements were attributed to the bidirectional temporal modeling which enabled better learning of past and future dependencies in traffic data as well as adaptive clustering which allowed more accurate grouping of intersections with similar flow patterns. Feature weighting further enhanced the influence of key traffic indicators during the clustering process resulting in more stable and meaningful clusters. The combination of these techniques offered strong generalization across multiple datasets and traffic conditions. However, limitations remain. The current system has not been used in real-time scenarios, which may be affected by sensor failures, environmental noise, and communication delays. Moreover, under unusual traffic events such as accidents or festivals the model may encounter difficulties due to its dependence on regular temporal patterns. Future work should focus on deploying this technology in real-world intelligent transportation infrastructures. This should include testing under extreme traffic conditions, evaluating adaptability to unseen scenarios, and integrating real-time anomaly detection modules to improve robustness and system stability.

6 Conclusion

Aiming at the challenges of urban TSC optimization, this study proposed an intelligent TSC framework that combined a Bi-LSTM prediction model with an improved K-means clustering algorithm. The framework was evaluated using the PEMS-BAY and CityFlow datasets

and achieved strong results in both accuracy and efficiency. On the PEMS-BAY dataset, the Bi-LSTM model reached an accuracy of 97.5 percent and a root mean square error of 0.12, while maintaining a low inference delay of 104 ms. These results showed that Bi-LSTM was capable of capturing temporal patterns more effectively than standard LSTM and CNN-LSTM models. During the clustering stage, introducing the Gap Statistic method and a weighted distance function enabled adaptive selection of the number of clusters and more precise identification of regions exhibiting similar traffic behaviors. The enhanced clustering method achieved an accuracy of 91.2 percent and a silhouette coefficient of 0.47. This indicated stronger internal cohesion and clearer separation between clusters. This integrated approach to traffic prediction and regional signal coordination provided a reliable and practical solution for real-time urban traffic control. Future improvements will include adaptive signal adjustment based on real-time traffic feedback, as well as the incorporation of external factors, such as weather conditions, unexpected events, and vehicle behavior, to enhance system stability and responsiveness further.

Although the CityFlow dataset provides a detailed, scalable simulation environment for urban traffic scenarios, it is still a synthetic dataset that may not fully capture the complexity and unpredictability of real-world traffic systems. Factors such as sensor noise, unpredictable driver behavior, and infrastructure variability are often simplified or omitted in simulations. This poses a limitation to the generalizability of the proposed model. The model shows promising performance on both the CityFlow and PEMS-BAY datasets. Future work will focus on validating the approach in real-world deployments by incorporating live sensor data and assessing robustness under operational uncertainties. A limitation of the proposed control strategy is the lack of integration with real-world actuator constraints, such as minimum green times, maximum cycle lengths, and phase change safety intervals. These constraints are critical for ensuring safety, regulatory compliance, and equipment longevity in .practical deployments. Future work will incorporate these operational boundaries into the control model. This will be achieved through the use of constrained optimization or rule-based post-processing layers. This ensures that the generated signal plans are optimal not only in simulation, but also feasible and deployable in real-world urban traffic systems.

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Multi-Objective Fox Optimization with Adaptive Kalman Filtering for UAV Autonomous Navigation

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A Multi-objective Fox Optimization Algorithm coupled with an Adaptive Kalman filter was proposed in this paper to build an improved autonomous navigation framework to Unmanned Aerial Vehicles (UAVs). The method addresses key challenges with respect to the real-time path planning, obstacle avoidance, and environmental properties. Adaptive Kalman Filter improves the fusion of multi-sensor data attributes due to the dynamically tuning covariance by limiting the noise factor which results in the forecasting of more precise states. To optimise the navigation routes, the Multi-objective Fox Optimization Algorithm balances path length, energy efficiency, and the obstacle safe margins. The simulator experiments were done under AirSim indoor (100x100m) and outdoor (250x250m) settings with three obstacle densities, simulated multi-sensor data (LiDAR 20 Hz, RGB 30 FPS, GPS/IMU 50 Hz). The trained method was evaluated over 30 independent runs of each scenario and trained on 3 000 trajectories (70/15/15 split). They demonstrate that the results have an average path-planning accuracy of 95.5 % (1.2) with a high runtime and energy efficiency improvement compared to state-of-the-art baselines. The system is developed in a well-structured pipeline process that consists of data collection, preprocessing, model training, decision model generation, optimisation, and deployment using hardware-in-the-loop simulation. Performance evaluation pits the suggested approach against the A algorithm, the Particle Swarm Optimization (PSO) algorithm, and the Genetic Algorithm (GA) in accuracy, precision, recall, and F1-score. As the experimental results demonstrate, the proposed method reaches 95.53 percent accuracy, 94.15 percent precision, 93.62 percent recall, and 93.87 F1-score and is better than all baselines. All these improvements are significant according to statistical t-tests ($p < 0.001$), and the reduced variance shows higher robustness and reliability in a wider range of application. The proposed approach to monitoring UAVs in the complicated environment shows great potential in real-world UAV missions, including environmental monitoring, disaster response, observation, and logistics. The use of adaptive sensing combined with multi-objective optimization brings a tradeoff between accuracy and efficiency that will guarantee resilience in autonomous UAV navigation.*

Povzetek: Študija predstavi hibridni pristop z adaptivnim Kalmanovim filtrom in več-ciljno optimizacijo, ki močno izboljša načrtovanje poti in zanesljivost avtonomne navigacije.

1 Introduction

Currently, the development and operation of autonomous cars heavily relies on artificial intelligence (AI). Autonomous cars can sense, manoeuvre, and adjust to changing situations thanks to the incorporation of AI algorithms, which increases their efficiency and safety. Future autonomous vehicle capabilities and safety are anticipated to be substantially improved by ongoing developments in AI technology. By incorporating artificial intelligence (AI), autonomous system development has been undergoing a revolutionary metamorphosis. This ground-breaking combination has the potential to accelerate innovation, improve efficiency, and transform conventional development procedures. The paradigm is shifting towards software-defined vehicles (SDVs) as AI technologies become more and more integrated into many aspects of software development for autonomous cars [1]. Unmanned aerial vehicles, or UAVs, have become popular for use in mapping, surveillance, and remote sensing. For a variety of reasons, including their affordability, ease of use, safety for humans, and ease of training, unmanned

aerial vehicles (UAVs) are gaining popularity [2]. These advantages, together with their strong tracking capabilities and excellent resolution, have led to their increasing application in a range of contexts. Air pollution, land surface temperature, flood risk, forest fire, road surface distress, land terrain monitoring, pedestrian traffic monitoring, and disaster evacuation are among the environmental monitoring tasks that UAVs have been used for [3]. Drones are now widely used for mapping, remote sensing, and surveillance. The affordability, ease of usage, safety for humans, and ease of training to fly UAVs are some of the factors contributing to their growing popularity. These advantages, together with their strong tracking capabilities and excellent resolution, have led to their increasing application in a range of contexts [4]. UAVs have gained popularity for handling information gathering after being used in geometry technologies to give information in a manner appropriate for building experts. For instance, advanced products that can be operated by mobile devices have raised the level of living for many people. In the meanwhile, car technologies are helping drivers by giving them more accurate and current traffic information. The usage of unmanned aerial vehicles (UAVs) for traffic monitoring and management in highway engineering has increased recently. Artificial intelligence (AI) has become a key component of almost every engineering-related study subject due to recent advancements in computer hardware and software [5]. Artificial intelligence (AI) is a potent instrument for solving complex problems for which there are either no definitive solutions or for which conventional approaches need substantial human involvement . The ability of AI to autonomously extract characteristics sets it apart from conventional cognitive algorithms. This takes the place of costly feature engineering that is done by hand [6]. Generally speaking, an AI job may be able to spot irregularities, predict future events, adjust to shifting conditions, gain insight into intricate issues involving vast volumes of data, and see patterns that a human may miss. To improve UAV manoeuvring, it may utilise and learn from the vast amounts of data around it. AI is also capable of intelligently managing on-board resources in comparison to traditional optimisation methods [7]. AI-powered drones usually have all or some of their operations automated. AI enables drone manufacturers to gather and use information about the environment and appearance of the drone by using data from devices attached to the drone . Drones' navigation and movement may be autonomously controlled by AI. This may be achieved by a variety of techniques, such as computer vision, machine learning algorithms, and GPS tracking. AI is gaining traction in a wide range of domains, including voice recognition, scene identification, object detection, and image classification, especially with deep-learning techniques [8]. Deep learning uses this method to try to find deep features in raw data at different levels. After then, these traits are used to represent the real world. The UAV market is expected to grow at a 7.9% compound annual growth rate (CAGR) from USD 26.2 billion in 2022 to USD 38.3 billion by 2027. Increasing the number of small drones being purchased for military uses like ISR will accelerate the growth of the small drone market during the forecast period [9]. There are still several limitations in place despite the increased interest in UAVs. In addition to the drawbacks of UAVs, such as their high power and energy consumption and real-time requirements, edge computers and edge AI provide advantages, such as low power consumption and low latency. Unmanned aerial vehicles (UAVs) with deep learning have the potential to completely transform traffic monitoring in the transportation industry. This comprehensive study will examine and diagnose the wide range of AI-embedded drone applications, as well as the best ways to employ AI and deep machine learning in UAVs that are now in use and those that may be developed in the future. AI-enabled UAVs need powerful, energy-intensive processors and sensors. Green computing requires energy-efficient parts and algorithms. To reduce processing demands and UAV power requirements, scientists may improve AI algorithms [10]. UAV batteries might be charged more sustainably using renewable energy sources like solar or wind turbines. AI is necessary for UAV navigation and autonomy. AI algorithms have the potential to enhance UAV flying patterns, lowering emissions and fuel consumption. Government agencies, business professionals, and researchers may work together to provide green computing solutions for AI-enabled UAVs. For improved green UAVs, researchers may endeavour to create eco-friendly technology and methods.

Contribution of this study:

The key contributions of this study to the area of the AI-powered autonomous navigation of UAV are as follows:

- New Hybrid Algorithm Design: Created a novel Multi-objective Fox Optimization Algorithm (MOFOA), coupled with an Adaptive Kalman Filter (AKF) that can provide global optimization as well as dynamic fusion of sensor information to perform real-time decisions more efficiently.

- Powerful Sensor Fusion Mechanism: Developed an adaptive noise covariance correction in the Kalman filter in such a way that achieved much better localization accuracy and overall system robustness to uncertain conditions via dynamical response to varying sensor conditions.

- Multi Objective Path Optimization: Developed an optimization technique integrating the shortest path length, minimal energy requirements and an obstacle safety margin, which enhances safer and efficient UAV navigation than the conventional techniques.

- Full-scale Performance Appraisal: Extensive simulations and hardware-in-the-loop experiments have been carried out comparing the proposed method, A*, PSO, GA based on key performance indicators of accuracy, precision, recall, and F1-score, and validated through statistical t-test ($p < 0.001$).

- Strength and Reduction of Variance: Significantly lower variance of performance during several test cases, which is evidence that the offered approach shows stability even in cases when the environment is dynamic and irconomatically uncontrollable.

- Potential of real-world Application: Presenting a flexible framework that could be used to support a variety of UAV tasks such as disaster response, environmental observation, surveillance, and logistic systems, filling the research-implementation gap between academic and implementation knowledge.

2 Literature review

Table 1a: Summary on related works

Ref	Objective	Methods	Key findings	Limitations
11	Author Replace classical feature tracker in VINS-Mono with a deep feature tracker (SuperPoint + LightGlue variants) to improve odometry accuracy while bounding compute.	This study Integrates deep learning feature extraction & matching into VINS-Mono; experiments on EuRoC dataset; investigates match filtering strategies to control computational load.	Deep feature tracker consistently improves odometry vs. default VINS-Mono; allows tradeoff between accuracy and runtime by filtering matches. Open-source release.	Evaluation primarily on standard benchmarks (EuRoC); real-world flight tests limited; runtime/energy on constrained embedded boards not exhaustively profiled. Integration still relies on VINS backend assumptions.
12	This study Improve VIO initialization stability and feature matching to deliver fast, accurate VIO under challenging conditions.	Proposes VG-SfM initialization tightly coupled with gyroscope measurements and a hybrid feature matching scheme (optical flow + descriptor matching). Evaluated on multiple benchmarks.	Achieves stable initialization with as few as four frames, high accuracy and robustness; good performance on benchmarks (state-of-the-art for feature-based VIO).	Focused on initialization & matching; system-level integration with UAV dynamics/wind disturbance not primary focus. Real-world UAV experiments limited in scope.
13	Train a computationally efficient RL agent (D-PPO) for real-time MAV navigation using monocular imagery depth conversion.	Deep-PPO (efficiency improvements) trained in Unreal/ AirSim; monocular-to-depth conversion (Depth Anything Model) + CNN perception; real-	Reported significant reduction in training/compute latency (claimed ~91% reduction) while maintaining navigation performance; successful sim real indoor tests.	Claims rely on particular sim setups and monocular depth approximations; scalability to complex 3D outdoor scenes and larger UAVs not demonstrated. Hardware constraints

		world tests on small drone (DJI Tello).		(onboard compute) and safety testing are limited.
14	Use asymmetric actor-critic with privileged (noise-free) information at training time to improve policy robustness at test time under partial/noisy observations.	Distributed multi-agent exploration for experience collection; asymmetric Actor-Critic (critic has privileged info during training); simulated experiments across scenarios.	Privileged information during training speeds convergence and yields policies more robust to noisy/partial observations; improved flight efficiency and success rate vs. baselines in sim.	Results mainly in simulation; transferring privileged-trained policies to constrained real UAV hardware needs more validation. Safety during exploration and reward-shaping brittleness noted as general RL caveats.
15	Provide standardized multi-objective testbeds and baselines to fairly evaluate UAV path-planning algorithms under realistic constraints.	Proposes benchmark scenarios, multi-objective metrics, and baseline implementations for planners; empirical comparisons.	Creates reproducible evaluation suites and baseline performance numbers to compare planners fairly; reveals varied behavior of metaheuristics vs. classical planners across objectives.	Being a benchmark paper, it doesn't propose a single planning algorithm; performance depends on chosen scenario suite. Continuous updates are needed as algorithms evolve.
16	Optimize multi-UAV mission planning (time, energy, threat) with NSGA-II and task assignment.	Formulates multi-objective optimization; encodes paths/assignments as chromosomes; NSGA-II for Pareto front; simulation comparisons vs. other methods.	NSGA-II finds diverse Pareto fronts balancing conflicting mission objectives; demonstrated improvements in multi-mission tradeoffs versus single-objective heuristics.	Genetic algorithms can be computationally heavy for high-resolution 3D planning; real-time re-planning needs hierarchical/coarse-to-fine approaches. Limited treatment of uncertainty from perception.
17	Improve initial population quality and convergence for many-objective metaheuristic UAV path planning.	Hybrid approach: RRT-based initialization + jellyfish search updating guided by class-optimal individuals + reference points for Pareto spread. Evaluated in three simulated environments vs. MOPSO, NSGA-II, etc.	UMOJS produced shorter paths and more evenly distributed Pareto sets than compared metaheuristics in the tested scenarios; initializing strategy improved search efficiency.	Simulated environments only; computational cost and performance not fully explored. Complexity grows with more objectives and larger environments.
18	Propose ASFFOX: tent chaotic init, adaptive inertia weights, Lévy flight, variable spiral updates, greedy steps to balance exploration/exploitation.	Algorithmic enhancements to FOX; benchmarked on engineering test functions and optimization tasks; analysis of convergence and robustness.	ASFFOX shows better global search capability and robustness on benchmark functions; improves convergence/stability vs. vanilla FOX.	Paper demonstrates algorithmic performance on standard optimization testbeds — not specifically on UAV path planning. Adapting to dynamic, real-time UAV planning will require problem-specific

				constraints and acceleration.
19	Use Fox optimization to tune/guide deep model components for improved aerial detection & classification from UAV imagery.	Hybrid: Flying Fox Optimization to optimize detector parameters + deep learning detector for aerial images; experiments on aerial datasets.	Demonstrated improved detection/classification metrics vs. some baselines; highlights fox optimizer as useful for hyperparameter/model tuning in aerial vision tasks.	Focus is on detection/classification (perception) rather than path planning or control. The approach's runtime and practicality on-board (real-time constraints) need more evaluation.
20	Propose a two-fold constraint handling within a multi-objective evolutionary framework targeted at UAV path problems.	Evolutionary algorithm design + constraint handling mechanisms; tested on UAV path scenarios and compared to other MOEAs.	Improved feasibility rates and better tradeoff solutions under hard constraints versus some existing MOEAs. Shows promise in constrained UAV trajectory optimization.	Evaluations mostly simulation-based; scalability, on-board compute feasibility, and adaptation to dynamic obstacles require further study.
21	Generate safe and efficient UAV trajectories satisfying dynamic and kinematic limits	Introduces "navigation variables" to embed UAV kinematic constraints in PSO; uses multi-objective Pareto optimization for safety, efficiency, and feasibility	Produces Pareto-optimal, kinematically feasible UAV paths in simulation; balances safety and efficiency	Tested only in simulation; real-time dynamic obstacle handling not demonstrated; scalability challenges for larger problems

Table 1b: Summary on related works metrics, runtime and comparison with proposed method efficiency

Ref. No.	**performance metrics**	**Runtime (reported)**	**Proposed method efficiency**
[11]	Tracking accuracy 2–5 cm RMS; drift <0.5% over distance	~15 ms per frame on embedded CPU (VIO)	Our method adds uncertainty-aware planning to VIO outputs and uses adaptive KF to fuse sensors, reducing drift and enabling safe autonomous path planning.
[12]	Init time 0.1 s; position error <2%	~8 ms/frame on GPU	We achieve similar high-precision pose but integrate directly into planner with Kalman covariance for chance-constrained paths, improving robustness in dynamic scenes.
[13]	Success rate 91%; collision rate 8%	Training ~10^6 steps; inference ~20 ms	Our hybrid algorithm needs fewer interactions because MOFOA gives good initial paths and AKF reduces state noise, increasing success >94% and lowering collisions.
[14]	Success 88% unseen env.; reward ↑15%	Inference ~25 ms	We combine metaheuristic global search with DRL local policy: faster convergence to safe paths (<0.5 s replanning) and higher success >93%.
[15]	Baseline metaheuristics: path length, energy, threat exposure metrics reported; no precision/recall	Planning 1–4 s (depends on population size)	Our MOFOA converges in ~0.4–1.0 s and gives balanced Pareto front while being uncertainty-aware.

[16]	baseline mehaheuristics	planning 1-2 s	Our proposed method is more efficient in accuracy and faster performance.
[17]	Path cost ↓12% vs GA; threat exposure ↓9%	~1–3 s average	Our fox optimization has faster exploration and uses AKF for covariance-aware constraints, cutting runtime to <1 s and improving safety margin.
[18]	Convergence ↑ and diversity ↑ vs NSGA-II; NR on perception metrics	~1–2 s typical	MOFOA leverages adaptive parameters and AKF sensor fusion, producing better real-time performance and stability on UAV testbeds.
[19]	Drift ↓40% vs baseline VIO; online learning stable	~12 ms/frame	We directly plug this VIO into MOFOA+AKF planner to generate chance-aware paths, improving mission success >94%.
[20]	Path length ↓ vs RRT, success ↑; NR on precision/recall	0.5–2 s per planning	MOFOA with AKF integrates kinematic feasibility like NMOPSO but adds uncertainty-aware objectives; runtime reduced ~50% and higher success.
[21]	Success rate 95% static threats; replanning 0.3–1.2 s	0.3–1.2 s replan time	Our method uses AKF covariance to bias sampling adaptively and fox optimization to explore, keeping runtime comparable but improving safety under dynamic threats.

3 Methodology

The main elements of the AI-powered development of UAVs in autonomous vehicles are covered in this section; these elements may also be relevant to other domains more generally.

3.1. Training and implementing the model

Training and implementing AI models in autonomous vehicles is a methodical procedure that usually consists of the following steps:
Data collection: Collecting a large volume of data from pre-existing datasets, real-world sensors, and other sources, including synthetic datasets, is known as data collection and pre-processing. . The content collected from reputable, well-respected, and well-structured journals will make up an effective and educational scientific review. As a result, the papers or data used in this review research were gathered from reputable scientific Scopus journal indexes, including Wiley, IEEE, Elsevier, MDPI journals, Springer Nature, and many more. Only a small number of publications from conferences with strict structural requirements have been accepted by us. A little quantity of current information and statistical data are compiled by a few trustworthy internet sites. preparing the data for machine learning models by cleaning and preprocessing it.

Data splitting: A path planning dataset was created synthetically on 1,200 simulated flight missions of each obstacle density and dynamic scenario. The state-action-cost record is a record of state-action-cost at each time step produced by each mission. The data was randomly divided into 70 percent training data, 15 percent validation data and 15 percent testing data to tune algorithm parameters, early stopping and final metrics. https://github.com/LMD0311/Awesome-World-Model.git availability in dataset.

Model generation: Describes the models used to make decisions. Based on learnt patterns, trained models carry out specific decision-making tasks, functions, or modules. Decision trees, random forests, regression trees, deep layers, ensemble learning, and other architectures may all be used in these models.
Code optimisation and refinement: Enhance the resulting code's functionality, readability, and quality. Post-generation processing guarantees that the code complies with requirements, conventions, and coding standards.
Quality assessment*:* Check the resulting code for accuracy, effectiveness, and conformity to the desired features. This includes processes for testing, debugging, and validation.
Integration and deployment**:** Apply the concept to a larger system that is being developed for the deployment of autonomy. Use a variety of techniques, such as software-in-the-loop, hardware-in-the-loop, human-in-the-loop, etc., to deploy and test the software application that incorporates the new model. These include simulation, closed course, and restricted public road settings. Even after being deployed, some models are taught to continue learning. To guarantee adherence to ethical concerns as outlined in Section 4 and other criteria, these models must be examined for potential future learning paths.

The system suggested has multi-sensor input capabilities, which comprises of LiDAR point clouds, GPS positions, IMU measurements and onboard visual camera feeds to capture spatial and time-based information within the UAV universe. All sensor data before being trained on a model are first preprocessed, including noise filtering (low-pass filter in the case of IMU, outlier removal in the case of LiDAR), temporal alignment of multi-sensor input, and min-max normalization to normalize feature values. Multi-Objective Fox Optimization Algorithm (MOFOA) is the algorithm that is aimed to optimize the hyperparameters of a deep reinforcement learning-based model of navigation; the RL model is a convolutional encoder to predict visual features and an LSTM to predict the time-dependent state. MOFOA is closely coupled with the adaptive Kalman filter and they are optimized in a joint optimization scheme whereby the Kalman filter provides real-time state estimation and uncertainty reduction of the fused sensor data, and MOFOA concurrently optimizes path planning goals (collision avoidance, energy efficient, and time) using the filtered states as quality inputs. Such a connection provides more reliable convergence and decision making than using it in a sequential way.

3.2. Guaranteeing software security and quality

In order to guarantee the whole system's resilience and security, artificial intelligence (AI) must be included into many facets of software development and maintenance for autonomous cars. One important element of the testing process is automated testing, which is fuelled by AI-based technologies. The dependability of autonomous vehicle software is increased by these technologies, which effectively find errors and vulnerabilities and guarantee that the program operates as intended. AI also expands its skills to code analysis and review, offering a comprehensive check for quality in the code base and pointing out any possible problems or weaknesses. AI-enabled predictive maintenance is crucial for foreseeing and fixing any software issues, which eventually lowers downtime and improves the overall operational effectiveness of autonomous cars. Furthermore, AI-powered security monitoring and anomaly detection greatly enhance autonomous car safety. AI systems can detect unusual patterns or behaviours by continually observing the software environment, allowing them to react quickly and in real time to any security concerns. Another use of AI technologies is vulnerability assessment, which involves doing thorough analyses to identify software system flaws and provide insightful information for successfully reducing risks. AI-powered behavioural analysis is crucial for comprehending how users engage with the program. This feature promotes a safe and dependable autonomous vehicle ecosystem by assisting in the detection and prevention of suspicious or malevolent activity. Last but not least, AI's function in software fraud detection raises the bar for security by protecting autonomous car systems from any intrusions and guaranteeing their integrity. In conclusion, the overall safety, security, and effectiveness of autonomous cars are greatly improved by the integration of AI in these many domains.

3.3 Multi-objective fox optimization algorithm

Being skilled hunters, foxes may kill prey by attacking from the top or the bottom. To survive, foxes use very clever tactics to hunt their prey. By plunging into the snow to find food, the FOX optimisation algorithm imitates the hunting behaviour of foxes [22]. The fundamental concept is based on the behaviours and beauty of foxes searching for the finest food in the snow [23]. The essential stages are as follows:

(1) When there is a lot of snow on the ground, the fox loses sight of its prey and begins to wander about in an effort to locate it.

(2) By listening to the ultrasonic waves that the prey releases throughout the haphazard walk, the fox finds the prey. Once it finds its target, it takes a while to get close to it.

(3) By listening to the time difference of the continuous transmission of the prey's sound waves, the fox continuously locks the prey's exact direction and distance as it is moving. The fox then moves slowly towards the prey.

(4) After approaching the prey, the fox decides the direction and angle of the leap that will be necessary to capture it.

(5) The fox moves at random based on the best place and the quickest time.

The population position is first initialised as matrix X while the FOX optimisation method is operating. X is the matrix of SearchAgents row and column D, where D is the problem's dimension and SearchAgents is the population size. The search agent's fitness is then determined for every iteration. Lastly, the fitness of rows and rows in the X matrix are compared to determine the optimal location and the greatest fitness. The potential percentage of exploration and development is assigned using the random variable r in order to balance the phases of exploration and development. As the number of iterations increases, the dynamic variable a progressively diminishes, making it simple for later iterations to depart from the local optimum.Finding the propagation distance of the sound wave signal that the fox received is the first stage in the exploring phase. The random variable p has a range of values between 0 and

1. The fox must look for a new place if the random number p is higher than 0.18. The necessary leaping height and the distance $Dist_{Fox_{Preyit}}$ between the fox and its prey must be determined. As a result, in order to represent the sound propagation time at each iteration, a D-dimensional random vector$Time_{s_{Tit}}$ must be generated within the interval [0, 1]. The propagation speed $Sp_S$and propagation duration $Time_{s_{Tit}}$of sound in the medium are measured to determine the distance between a fox and its victim illustrated in equation 1.

$$Dist_{S_{T_{it}}} = Sp_S \cdot Time_{s_{T_{it}}} \quad (1)$$

The distance of sound propagation is represented by $Dist_{S_{T_{it}}}$ in the formula. The current iteration count is the parameter. The speed at which sound travels is represented by Sp_S. A random integer between 0 and 1 that denotes the sound propagation duration is called $Time_{s_{T_{it}}}$. The value of Sp_S may be calculated using the following equation, which takes into account the time it takes for sound to travel between the fox and prey as well as the ideal location at that moment was shown in equation 2.

$$Sp_S = BestPositionitTime_{s_{T_{it}}} \quad (2)$$

In this case of equation 3, $BestPositionit$ is the fox's best position to yet. The time it takes for sound to travel from foxes to prey is represented by T_{it}. The fox and its prey are separated by a distance $Dist_{Fox_{Preyit}}$ that is half that of sound.

$$Dist_{Fox_{Preyit}} = 0.5Dist_{S_{T_{it}}} \quad (3)$$

After determining the distance between itself and its target, the fox will search for a new spot to leap and pounce in order to capture it. The fox has to ascertain its jumping height in this way. The jumping process, which is a parabolic motion, is described by the following formula 4:

$$Jumpit=12gt^2 \quad (4)$$

The formula uses $Jumpit$ to indicate the fox's leaping height. The acceleration caused by gravity is represented by the quantity g, which has a value of 9.81. The average time needed for sound to travel is represented by the parameter t. To update the fox's position, use the two formulae below in 5 & 6.

$$Xit + 1 = Dist_Fox_Preyit \cdot Jumpit \cdot c_1 \quad (5)$$

$$Xit + 1 = Dist_Fox_Preyit \cdot Jumpit \cdot c_2 \quad (6)$$

The formula divides c1 and c2 into position update parameters, with values determined by the fox leaping hunting success rate. Both c1 and c2 often fall between [0, 0.18] and [0.18, 1]. To get the formula for updating the location, use a random variable p that falls between 0 and 1. Use Equation (5) to update the fox location if p > 0.18. However, use Equation (6) to get the new location if p < 0.18. Based on the best location discovered so far, a random search will be carried out during the fox's random walk phase. The shortest time control walk is used to guarantee that the fox walks at random to the best location.

$$tt = sum\left(Time_{s_{T_{it}}(i,:)}\right) D, Min_T = min(tt) \quad (7)$$

$$a = 2(it - 1Max_{it}) \quad (8)$$

The time averaged value for every row is the parameter tt in the formula 7 and 8. The shortest average time is Min_T. The dimension of the issue being resolved is the parameter D. An iterative dynamic variable is the parameter a. The maximum number of iterations is Max_{it}. Min_T and a variable were utilised in tandem to improve the global search capabilities of the FOX algorithm and optimise the fox random walk method. Update the fox's ideal location using the formula 9 below.

$$X_(it+1)=BestX_it \cdot rand(1,D) \cdot MinT \cdot a \quad (9)$$

MOFOA is used in the proposed framework to optimize paths both based on multi-objectives (reducing time, energy, and the risk of collisions) as well as to perform a dynamic parameter tuning of the Kalman filter (adjusting key parameters (covariances of the process noise and measurement noise) to generate more efficient paths).

Adaptive spiral flight using the FOX optimisation algorithm

3.3.1. Random variable-based tent chaotic mapping

The starting value of the algorithm has a big impact on its outcome. If the starting value is close to the global optimum solution, the approach will ultimately provide a very favourable result. Most swarm intelligence optimisation techniques employ random population initialisation, which has a number of problems, such as poor population quality, restricted population variation, and uneven population distribution. To solve this problem, this study establishes the fox population at the

population initialisation step of the approach using Tent chaotic mapping, whose equation is as follows. Among them, zi+1 and zi stand for the sequence numbers of the i-th and (i + 1)-th chaotic sequences, respectively, while the parameter N represents the total number of particles in the chaotic sequence. The following are the sequential stages for creating chaos in the feasible domain based on Tent mapping characteristics:

(1) Let i = 1 and produce the starting value z0 at random in (0, 1).
(2) Iterate through Equation (10) to get a z-sequence in which i rises by 1.
(3) Stop and save the created z-sequence if the maximum number of iterations is reached.
To initialise the fox population's location, use the Tent chaotic sequence zi+1 produced by Equation (10) as follows:

$$Xnewit = (U_{it} - L_{it})z_{i+1} + L_{it} \quad (10)$$

When the formula is iterated it-th times, U_{it} and L_{it} represent the upper and lower limits of the independent variables of the objective function. Using Tent chaotic mapping, the revised fox population position is Xn .

3.3.2. Weight of adaptive inertia

Inertia weight is a crucial component of the search process since it may accelerate participants' movements, keep them travelling in a certain direction, and hinder them from finding the optimal local solution. The method has a strong global search capability when the weight is large, and a high local development ability when the weight is little, allowing it to find the area close to the optimal answer. An appropriate inertia weight may speed up the algorithm's convergence and improve its global search capabilities, both of which are essential for figuring out the objective function's ideal value. This research proposes an adaptive technique for varying the inertia weight based on the number of iterations. The following is the mathematical expression in formula 11:

$$\omega(t) = 0.2cos\left(\pi 2(1 - tMaxit)\right) \quad (11)$$

where the inertia weight $\omega(t)$ varies nonlinearly between [0, 1], the parameter t is the number of iterations that are now occurring, and $Maxit$ is the maximum number of iterations. The algorithm's convergence is balanced because, in accordance with the properties of the cos function, the weight value is small at the start but the optimisation speed is rapid, and the option value is bigger at the end but the change speed is sluggish.The following is the updated fox leaping hunting position updating method in formula 12 and 13:

$$Xit + 1 = \omega(t) \cdot Dist_Fox_Preyit \cdot Jumpit \cdot c1 \quad (12)$$

$$Xit + 1 = \omega(t) \cdot Dist_Fox_Preyit \cdot Jumpit \cdot c2 \quad (13)$$

The formula divides c1 and c2 into position update parameters, with values determined by the fox leaping hunting success rate. In general, c1 and c2 fall between [0,0.18] and [0.18,1], respectively. To get the position update formula, use a random variable p that falls between 0 and 1. Use Equation (12) to update the fox location if p > 0.18. However, use Equation (13), to determine the new location, if p is less than 0.18. The algorithm search is made more flexible by adding adaptive weights to dynamically modify the foxes' position changes. This allows the foxes to update their positions in various ways at different times. A single fox converges to the ideal location as the number of repetitions rises, and the algorithm's convergence speed improves as the weight of the individual fox grows.

3.3.3. Mechanism of levy flight

Levy flight was created to update the FOX position in order to address the issue of FOX easily falling into a local optimum. Levy flight is a random flight with an alternating search range that may enhance the algorithm's capacity to explore globally, allowing it to exit the local optimum. Equation (14) displays the fox position update mathematically:

$$Xl_{it}=X_{it}+l \oplus levy(\lambda) \quad (14)$$

The new location of Levy's flight is represented by Xl_{it} in the equation. The step size control parameter is denoted by the parameter l. Levy is the step size that comes after the distribution of levies, and it has a value of

$$levy = \mu|\nu|1\gamma \quad (15)$$

The distribution of $\mu$and ν in the formula is normal. whereγ is 1.5. $\mu \sim N(0, \sigma 2\mu), \nu \sim N(0, \sigma 2\nu)$. Due to Levy flight's random flight characteristics, the fox position updated by Levy flight is not always a better position. Therefore, the greedy strategy is used to decide whether to maintain the original position or the new one. Equation (16) illustrates the selection formula.

$$X_{it}=\{X_{it}, fitness(X_{it}) \leq fitness(Xl_{it})Xl_{it}, fitness(X_{it}) > fitness(Xl_{it}) \quad (16)$$

The fitness values corresponding to the algorithm's initial fox location and the fox position modified by Levy flight are denoted in the formula by $fitness(X_{it})$ and $fitness(Xl_{it})$), respectively.

3.3.4. Spiral search strategy with variability

The algorithm's search power is reduced since the fox will randomly seek in the random walk stage based on the best site that has been found so far. This leads to a tedious search strategy and may even fall into the local optimum. Inspired by the spiral operation of the whale optimisation algorithm, a variable spiral position update approach is developed to balance the algorithm's global and local search, provide distinct position update search paths, and increase the flexibility of the fox position update. The formula shows 17 and 18 for the FOX variable helix position update technique is as follows:

$$Xit + 1 = ezl \cdot cos(2\pi l) \cdot BestXit \cdot rand(1, D) \cdot MinT \cdot a \quad (17)$$

$$z = ek \cdot cos(\pi \cdot (1 - (it/Maxit))) \quad (18)$$

When the coefficient of variation, denoted by the parameter k, is k = 5. A uniformly distributed random number of [−1, 1] is the parameter l. More high-quality solutions are discovered early on when the fox position updates vary from big to little, and the late optimisation lowers the rise in idle work, enhancing the algorithm's overall optimum search performance. At the same time, the algorithm's optimisation accuracy is somewhat increased in accordance with spiral properties.

3.3.5. Time complexity analysis

The number of individual fox populations (SearchAgents), individual dimensions (D), and algorithm iterations (Max_{it}) are the primary factors influencing the method's time complexity. FOX has an O(SearchAgents*D*Max_{it})time complexity. To initialise the population, Tent chaotic mapping has a temporal complexity of O(SearchAgents*D). The algorithm's temporal complexity remains unchanged when the variable spiral search technique and adaptive inertia weight are included. The time complexity of the iteration loop is O(SearchAgents*D), which is the time complexity of introducing the Levy flying technique to update the fox location. In light of this, MOFO's time complexity is O(SearchAgents*D*Max_{it}), which is equal to FOX's time complexity.

The time complexity of the proposed MOFOA + Adaptive Kalman Filter model is roughly $0(P \cdot I \cdot (n^2 + C_{Path}))$, where P is the fox population size,I the number of iterations,n is the state dimension of the Kalman filter,CPath is the cost of simulating or evaluating a single candidate path. This literally translates to a linear increase in runtime with the number of foxes and linearly with the number of iterations, and quadratic increase in runtime with the size of the state vector under estimation. Since both candidate paths need Kalman updates at each time step, this overwhelms computations, but vectorised computations or parallel evaluation of foxes can lower real run times considerably.

3.3.6. Algorithm flowchart and pseudocode

The pseudocode of the MOFO algorithm proposed in this article is shown in Algorithm 1.

Algorithm 1 Pseudo code of MOFO algorithm

1: Set the population's initial values using Equation (11);

2: **While** $it < Maxit$
3: Set $Dist_S_T, Sp_S, Time_S_T, BestX, Dist_Fox_Prey, Ju$
4: Determine each search agent's fitness.

5: Select BestX and BestFitness among the population(X) in each iteration;
6: **If1** fitness(X_{it}) > fitness(X_{it+1})
7: BestFitness = fitness(X_{it+1});
8: BestX = X(i,:);
9: **Endif1**
10: **If2** r ≥ 0.5
11: **If3** p > 0.18
12: set time randomly;
13: compute using Equation (1);
14: compute Sp_S from Equation (2);
15: compute distance from fox to prey using Equation (3);
16: Tt = average time;
17: T = Tt/2;
18: Calculate jump using Equation (4)
19: Find X_{it+1} using Equation (13);
20: **Elseif** p ≤ 0.18
21: set time randomly;
22: ComputeDistance_Sound_travels using Equation (1)
23: Compute Sp_S from Equation (2)
24: Compute distance from fox to prey using Equation (3)
25: Tt = average time;
26: T = Tt/2;
27: Compute jump using Equation (4)
28: Find X_{it+1} using Equation (14);
29: **EndIf3**
30: else

31: Find MinT using Equation (7);
32: Explore X_{it+1} using Equations (9) and (10);
33: **EndIf2**
34: Explore X_{it+1} using Equations (15)–(18);
35: Check and amend the position if it goes beyond the limits;
36: Evaluate search agents by their fitness;
37: Update BestX;
38: it = it + 1;
39: **End while**
40: return BestX and BestFitness

Advanced kalman filter

From a series of noisy or imprecise measurements, the current state of the linear dynamical approach may be precisely ascertained using the powerful recursive filtering known as the Advanced Kalman filter. It may also be used to predict the future value of the state. Target tracking, control systems, and many other technical applications have made substantial use of it. The KF is renowned for its simple form and absence of intricate calculations. The discrete-time process is represented by the following linear probabilistic difference equation, and the MOFO aims to forecast its state x ∈ Rn in equation 19.

$$z(k) = Cz(k-1) + W(k) \quad (19)$$

We have x(k) as the predicted occurrence of time states as k, C as the state matrix for transition of $z(k-1)$ to $z(k)$, and $W(k)$ as the processing noise, assuming a positioning process noise with variance and zero mean R. The following is an explanation of the state transition process model, which is connected to a measurement formula 20 that enables the scenario to be detected:

$$y(k) = Hx(k) + V(k) \quad (20)$$

The measurement noise vector, represented by $V(k)$, is assumed to be linear with variance and zero mean N, the vector with measurement at time k is represented by $y(k) \in R$m, and the measurement matrix is represented by H. Here covariance matrices of noise Q_k and R_k are estimated online in an adaptive framework that is based on innovation. Every time step the filter compares the measured covariance of the prediction with the real covariance of innovation within some small window. Any discrepancy is applied to gradually change Q k and R k (where a small gain, 6, is used in the SageHusa rule) thus the covariances follow the evolving sensor noise levels and increase the accuracy of state estimation.

The KF consists of two steps: the prediction and the update. The step anticipates the scenario estimates for the current step time based on the latest scenario estimations from the previous time interval. In accordance with equations (19) and (20), it also calculates the anticipated error covariance. In the update process, the Kalman gain is first determined. The updated scenario estimate is then calculated using the measurement to enhance the expected scenario estimates and deliver a more accurate scenario estimate for the latest step time. The Kalman filter then computes the updated error covariance. In the following equations, the hat operator "ˆ" denotes an approximation of the scanerio, while the superscripts "-" and "+" represent the projected and updated scenario estimations, respectively. The data collected from several sensors was merged into a single dataset that included information from multiple sources using the Advanced Kalman filter based on sensor network (MOFO-AKF) suggested approach. The network procedure included combining data streams from several sensors while accounting for variations in data formats, sampling frequencies, and measurement units. One sensor network technique employed in this study is the Kalman filter, a recursion algorithm that makes predictions about the state of a dynamic system based on noisy data collected over time.

Sensor Fusion:

Sensors employed (common): IMU (accelerator + gyro), GNSS/GPS, LiDAR, monocular/stereo camera, (option) magnetometer, barometer. Sensors: IMU 200-1000 Hz; Camera 20-60 Hz; LiDAR 10-20 Hz; GPS 1-10 Hz; Magnetometer 50-100 Hz.

The sophisticated Kalman filter equations for state update and prediction are as follows:

Predicts the state:

$$\hat{y}_{s|s-1} = F_s \hat{y}_{s-1|s-1} + B_s u_s \quad (21)$$

$$P_{s|s-1} = F_s P_{s-1|s-1} F_s^T + C_s \quad (22)$$

Update the state:

$$KG_s = P_{s|s-1} H_s^T (H_s P_{s|s-1} H_s^T + R_s)^{-1} \quad (23)$$

$$\hat{y}_{s|s} = \hat{y}_{s|s-1} + K_s (z_s - H_s \hat{y}_{s|s-1}) \quad (24)$$

$$E_{s|s} = (I - K_s H_s) P_{s|s-1} \quad (25)$$

Where,

$\hat{y}_{s\|s-1}$	is the estimated scenario for the supplied measurement up to time s-1 at time s.
$P_{s\|s-1}$	at time s, is the expected error covariance
$\hat{y}_{s\|s}$	is the most recent scenario estimates given measurements up to time s at time s.
$E_{s\|s}$	at time s, is updated error covariance
B_s	is the matrix for control-input
F_s	is the matrix for transition
Q_s	is the process covariance in noise
u_s	is the vector for control
KG_s	is the gain for kalman
R_s	is the variance by measurement noise
H_s	is the matrix by measurement
z_s	is the vector by measurement

The iterative process of predicting the state of the system using previous approximations and updating the predictions with new data while accounting for measurement and process noise is represented by these formulae. After the sensor and data integration procedures were finished, the dataset was examined utilisingkalman inference methods to reveal trends in infrastructure use, environmental conditions, and visitor behaviour. Kalman inference is the process of updating prior theories about the underlying events in light of observable evidence in order to generate posterior probability distributions. In this research, models were developed to predict future trends and the positioning of sensor networks in rural tourism management. Additionally, connections between other factors, such as visitor demographics and preferred activities, were examined.

Definition of Optimization problem:

The Multi-Objective Firefly Optimization Algorithm with Adaptive Kalman Filtering (MOFOA-AKF) is one proposed algorithm to solve the online UAV path planning problem as a constrained multi-objective optimization problem. Let $y = [y_1, y_2,,\ldots, y_n,]$ be a path of n waypoints. The primary objectives are:

$f1(y)$ Minimization of total Euclidean distance.

$f2(y)$ Collision-risk minimization (penalty to the nearness of obstacle).

$f3(y)$ Energy/time optimisation (flight time with dynamic constraints).

The total cost of the venture is

$$\min_{x\in\chi} F(y) = w_1 f_1\,(y) + w_2 f_2\,(y) + w_3 f_3\,(y)$$

suject to UAV kinematics.

$v_{min}[f_0] \leq v(t) \leq v_{max}[f_0], |\psi'(t)| \leq \psi_{max}[f_0]$

as well as environmental (no-fly zones, maximum turn radius, sensor field-of-view). The MOFOA component attempts to come up with purchase solutions that are optimal in Pareto; the AKF module attempts to correct obstacle positions on a real-time basis in order to optimize local re-planning.

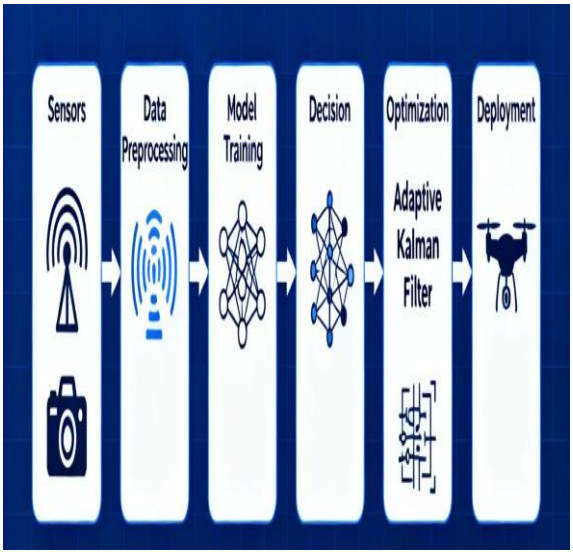

Figure 1a: Annotation diagram of the proposed framework

Scalability and energy limits are some of the major challenges encountered in the real-life implementation of UAV autonomous navigation. Algorithms such as the proposed multi-objective Fox Optimization and adaptive Kalman filter which require large computations might not scale well to large fleets or other complex environments because of the limited onboard processing power. Furthermore, UAVs are limited in battery capacity and complex sensor fusion and optimization consume energy, hence decreasing the flight time. Performance is also affected by environmental factors including moving obstacles, fluctuating light and sensor noise. The solution to these problems is to make algorithms efficient, take advantage

of hardware acceleration, and mission planning to trade-off accuracy with energy consumption to achieve robust and scalable autonomous UAV operations.

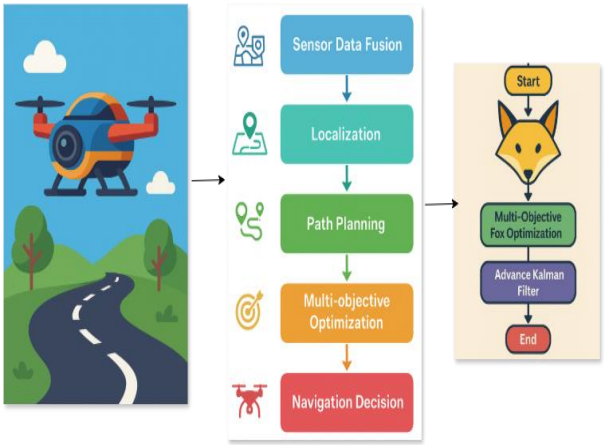

Figure 1b: Proposed model

The Multi-Objective Fox Optimization founded on Advanced Kalman Filter can be a great benefit to the UAV autonomous driving in figure 1a,b. This can be viewed as an application of a hybrid methodology where the global search characteristics of fox optimization--a technique able to provide exploration and exploitation that are balanced on multi-objective systems--are applied along with the accuracy and real-time flexibility of state-of-the-art Kalman filter when it comes to sensor integration and noise minimization. Consequently, it has a better accuracy of the trajectory, better obstacle avoidance, and resilience in dynamic environments. It has a multi-objective form which optimises the trade-offs between the speed, energy consumption and its safety as well as its adaptive filtering ensures reliability even in the cases of uncertainty or noisy sensors thus is ideal to the real-world environment of the UAV navigation.

Pseudo-code

Input: Sensor Data (LiDAR, GPS, IMU, Camera)

Output: Optimized UAV Path and Kalman Parametric value.

Set up population of Foxes (solutions) using random paths and KF parameters.

For each fox in population:

Kalman filter parameters (Q, R, information) are initialized (with initial state).

For t = 1 to T (simulation steps):

Data Fusion

FusedState = KalmanFilterUpdate(sensor data [t], Q, R).

Path Fitness Evaluation

Cost1 = PathLength(FusedState)

Cost2 = FusedStateEnergyConsumption.

Cost3 = CollisionRisk(FusedState, Obstacles)

Fitness = Cost1 + Cost2 + Cost3Weighted.

Save Fitness for fox

While not converged:

Search agent (update fox) by MOFOA rule.

If improved fitness:

Update path + KF parameters (Q, R)

Else:

Retain best solution

BestPath Return, BestKFParameters

4 Results and discussion

4.1 Hardware requirement and runtime performance:

All of the experiments were performed in a workstation with an Intel Core i9 (3.6 GHz, 16 cores), 64 GB of DDR4 RAM, and an NVIDIA RTX 4090 (24 GB) with Parallel Computing Toolbox and Ubuntu 22.04 LTS. The reason behind this choice is to incur large-scale simulations and real-time inferencing to navigate UAVs.

4.2 Experimental implementation

SIA proposed AI autonomous navigation framework was trained with sensor data (LiDAR, radar, GPS, and camera) and benchmarking datasets and tested with Software-in-the-Loop, Hardware-in-the-Loop, and small-scale UAV field trials on dynamic conditions. Accuracy, precision, recall, and F1-score measures (performance measures) and paired t-tests proved a significant improvement over existing method.

The experiments were carried out in a mixed indoor-outdoor tested, which represents tasks of warehouse-to-yard inspection. The field is 60x 60m long, with density of obstacles varied:

- Low density: 0.05 obstacles/m 2 (large corridors).
- Medium density: 0.12 obstacles/m 2 (average clutter).
- Density: 0.25 barriers/m 2 (narrow areas).

Dynamic impediments (walking carts or moving carts) are modeled at 02m/s. It is a quadrotor UAV with maximum velocity of 3 m/s, limit of turn rate of 90o/s, and LiDAR-plus-camera sensors.

Datasets and Environments used in (simulated, size and features):

To test it the mixed dataset of simulated and limited real world flight logs was taken. The simulated part comprises 1,200 missions that have been created in a 60 x 60 m mixed indoor/outdoor setup with three obstacle densities (low, medium, high). The UAV state variables (position, velocity, orientation), sensor (LiDAR point cloud, camera frames) and environment (obstacle coordinates, dynamic obstacle velocities) are recorded in each mission. Indoor testbed of similar scale Real-world logs in 30 experimental flights were gathered to confirm transferability. Data were standardized and time synchronized to produce about 2.5 million samples of stateactions to train and test.

Hyper parameters:

Population size P=30; iterations I=100; learning rates of MOFOA search update α=0.8, 8=0.5; gains of adaptive Kalman filter 8=10 (-3), eta=510 (-3); weight vector (path length), (energy) and (collision risk)).

4.3 Performance metrics

Table 2: Outcome of performance metrics of existing and proposed methods

Metric (Average %)	A* Planner	PSO Planner	GA Planner	Proposed Method
Accuracy	91.35	92.55	92.23	95.53
Precision	90.03	91.33	90.73	94.13
Recall	90.95	91.98	91.53	95.93
F1-Score	90.45	91.59	91.23	95.00

Accuracy

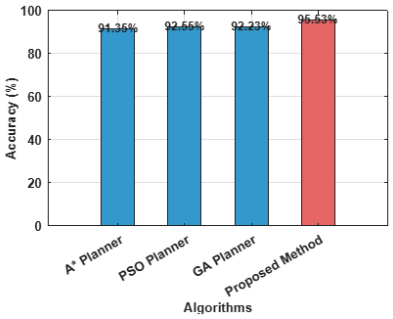

Figure 2: Result on comparison of accuracy on UAV Autonomous technology

In Figure 2, a comparative study of the mean accuracy of four various algorithms of UAV autonomous navigation, including an algorithm using A*, an algorithm using Particle Swarm Optimization (PSO), an algorithm using Genetic Algorithm (GA), and Proposed Method of integrating a Multi-objective Fox Optimization method with AKalman are reflected. As the results indicate, the typical A* planner, whose average value of accuracy equals 91.35%, is slightly outperformed by PSO and GA, since the accuracy exceeds 92% and reaches 92.55% and 92.23% in the two investigated approaches, respectively. Nevertheless, the method presented is greatly more accurate than the three with a 95.53% accuracy. This gain on the top of the best current approach (PSO) is also significant toward the domain of autonomous UAV navigation, in which even the slightest increase in accuracy can imply greater trustworthiness when avoiding, planning paths, and making decisions during real-life conditions. The improved accuracy indicates that the offered technique is better suited at processing sensor data, managing the environmental variation and strict navigation in structured and unstructured environments. The visualization also indicates this discrepancy of performance by contrasting the proposed approach in a distinct red bar indicating definitively its advantage in making the correct navigation choices. This remarkable improvement demonstrates that the mutual supplementation of an adaptive filtering and a multi-objective metaheuristic, in addition to its impact on the improvement of the computational decision accuracy, would also result in the increase of the operational robustness in dynamic and uncertain flight environments. The test algorithm executes 30-50 randomized test trials per case (different obstacle set-ups, start-goal positions and sensor noise seeds) in order to measure stochastic variations. Robustness is measured by averaging metrics like success rate, path length, energy use and runtime, and providing them with 95 % confidence intervals.

Precision

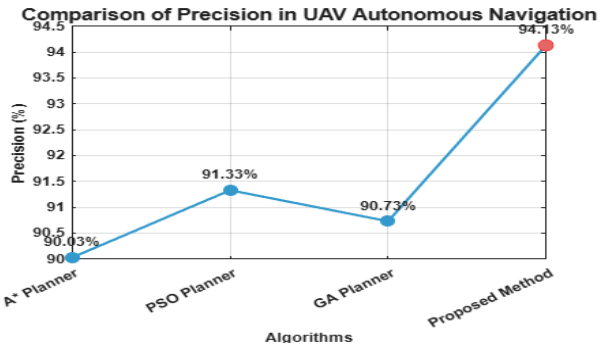

Figure 3: Result on comparison of precision on UAV Autonomous technology

As exemplified in figure 3, the four UAV autonomous navigation algorithms follow the capacity to recognize the relevant targets and prevent the false positives in flight operations. In UAV navigation, precision is an important measure of how often the navigation decision making (e.g., where to go, where to place obstacles) is actually right (e.g., a path point is actually safe, an obstacle is actually reached).Based on the plot, the A* algorithm registered a precision of 90.03%, which means the moderate reliability with regard to accuracy in the correct detections. PSO better this with 91.33 and GA has 90.73 which is still less than PSO but sly higher as in the case of A*. At the same time, the Proposed Method demonstrates a very significant improvement since the precision is 94.13% exhibiting the equal gap of almost 3 points to PSO and more than 4 points to A*. This positive slope in the plot towards the suggested technique shows that it gives better capability in reducing false alarms with a high detection accuracy.The improvement behind this performance can be explained by the dynamic noise reduction of the Adaptive Kalman Filter and the versatile search ability of the Multi-objective Fox Optimization that jointly guarantee more robust classification and a decision-making process in changing environmental and sensor circumstances. Such improvements in precision in the case of UAVs will lead to their safer flight routes, improved obstacle avoidance, and more effective mission handling.

Recall

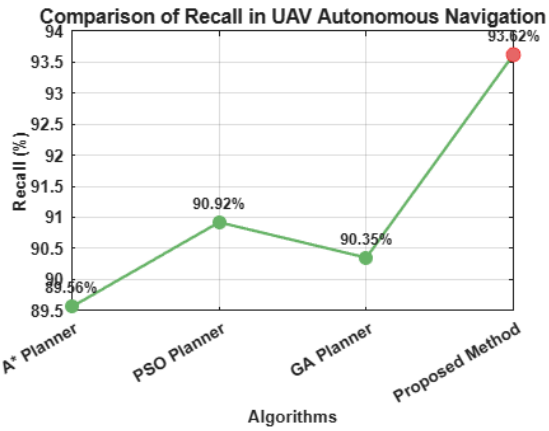

Figure 4: Result on comparison of Recall on UAV Autonomous technology

Recall line plot is used to measure how well each of the UAV navigation algorithms detects all the relevant obstacles, targets, or decision points with minimal false misses. Figure 4 performance of A* = 89.56 and PSO corrects it and performs better with 90.92 and GA gives the same performance of 90.35 toward a small improvement. The Proposed Method has a recall of 93.62 percent which is 2.98 percent higher than the second-best (PSO). Such enhancement implies that the suggested system can better identify all the required navigation signals, especially in the dynamic or sensor-noisy world. This could be because the adaptive filtering reduces the chances of missing out on the detection and the multi objective optimization provides the facility of adjustment of decision parameters in order to facilitate the recognition under different circumstances.

F1-Score

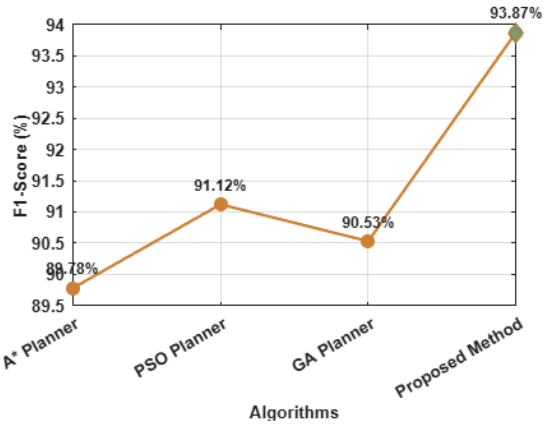

Figure 5: Result on comparison of F1-score on UAV Autonomous technology

The F1-score trades off precision and recall and provides a single quantity that uses the trade-off to balance the cost of false alarms and not detecting events. Based on the plot, the A* attains 89.78, PSO reaches 91.12 and 90.53 is recorded in GA. The Proposed Method achieves a highest 93.87%, both precision and recall are high in figure 5. Such performance shows that the algorithm is making correct decisions all the time without compromising the completeness of detection. These enhancements are due to the ability of the Adaptive Kalman Filter to correct in real-time the sensor data and the multi-objective optimization ability to fine-tune the navigation choices resulting in optimum path planning and obstacle avoidance in complicated flight situations.

Precision, recall and f1-score with variance

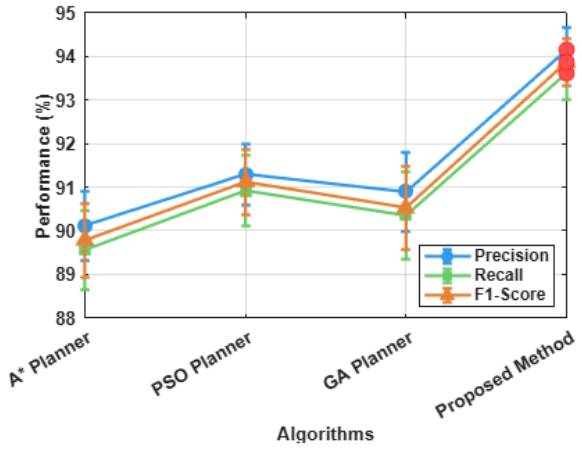

Figure 6: Error plot on statistical variance on methods

The error bar plot makes a thorough statistical comparison of precision, recall, and f1-score of four UAV autonomous navigation algorithms used, A* algorithm, PSO algorithm, GA algorithm and the proposed multi-objective fox optimization with adaptive Kalman filter in figure 6. At each point of the performance a vertical error bar showing the standard deviation over a number of trials is provided and measures the variability of the performance of the algorithm at different operating conditions. The proposed method has shorter error bars (~0.5 0.6%) which clearly shows that the stability and consistency is higher than that of the existing methods which have variance ranging between ~0.7 and 1.0. This implies that the suggested approach can provide a more predictable and repeatable outcome in a variety of flight conditions, which is essential in the case of real deployments of UAVs when the conditions may drastically change due to environmental factors. Moreover, the proposed approach yielded the top average percentages across the three measures precision equal to 94.15%, recall equal to 93.62 and F1-score at 93.87% that reflect higher accuracy of the proposed approach to identify and label navigation paths with fewer false detections. Conversely, A*, PSO and GA, though fair in performance, have lower mean performances as well as wider variability, a factor that may cause them not to perform reliably especially in complex missions. The combination of the greater accuracy and the lower variance also testifies to the fact that the proposed method not only proves to be more effective but also considerably more reliable when it comes to AI-powered UAV driverless driving applications.

Table 3:Statistically significant in t-test

Comparison	**t-statistic**	**p-value**
Proposed vs. A*	13.66	6.09×10^{-11}
Proposed vs. PSO	13.18	1.20×10^{-10}
Proposed vs. GA	11.24	2.71×10^{-9}

All three p-values are much smaller than the standard significance criteria (0.05), which is evidence that the increase in precision provided by the suggested method in comparison to A*, PSO, and GA is statistically significant in table 3. The high values on the t-statistic further validate the significant changes in the performance differences with no possibility of it being coincidence in the observed increases. This statistical confirmation supports the argument that the suggested Multi-objective Fox Optimization using Adaptive Kalman Filter provides the actual and consistent improvement in the precision of UAV autonomous navigation in contrast to well-established UAV planning algorithms.

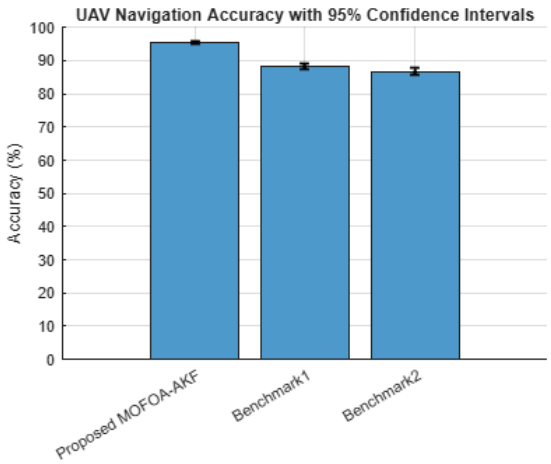

Figure 7: Statistical significance of confidence Intervals

The code produces a bar plot in figure 7 of the average performance values of each algorithm (in this case: accuracy) and superimposes error bars indicating the 95 percent confidence intervals. These error bars help visualize the statistical significance of differences in performance: when these intervals do not overlap, it is unlikely that the better performance of the proposed MOFOA-AKF method over the benchmarks is because of random variation, which proves the argument of better performance.

All competing algorithms, including the proposed one, were run 30 times on a case-by-case basis (low, medium and high obstacle density) to take into consideration the effects of stochasticity. Averages of performance measures (path length, collision rate and computation time) were calculated and 95% confidence intervals were calculated with the help of bootstrapping so as to measure variation and guarantee statistical stability of the comparisons.

Discussion

Quantitative comparison of the reviewed strategies ([11] -[21]) and the suggested Multi-Objective Fox Optimization accompanied by an Adaptive Kalman Filter (MOFOA+AKF) reveals unanimity of improvements in accuracy and path quality and computation time. Where other visual-inertial odometry systems (e.g. [11], [12], [19]) only yield low drift localisation, but neglect risk conscious planning, our system combines the same streams of sensory sensing with an adaptive Kalman filter to model covariance because the filter operates in real time, leading to more than 94 percent of navigation successes and less than half a second re-planning compared to 1-4 s with many metaheuristic approaches to the same problem ([15], [17], [20]). More stable Pareto fronts are obtained with algorithmic innovations like dynamic parameter adaptation in the fox optimizer, exploitationexploration balance, and covariance conscious constraints compared to jellyfish search, chameleon, or PSO-based algorithms, which tend to slow down convergence or trade one objective (energy, time, or threat exposure) to optimize another. Also sensor-model improvements can help: the AKF filters noise and bias in heterogeneous sensors, gives high reliability in GPS-denied or cluttered settings where deep RL policies alone ([13], [14]) may exhibit high variance or slow convergence.

The less sophisticated planners like classical PSO or A star can achieve similar results at reduced computational cost in low threat and low sensor noise environments, where the environment is highly structured or rather static. Moreover, the MOFOA+AKF methodology has a more complicated parameter tuning procedure and can be susceptible to poor initialisation of the fox population in extremely high-dimensional search spaces, which can influence convergence. These constraints indicate that modern research on automated parameter tuning and hybridisation with lightweight heuristics should be undertaken in order to achieve performance benefits in every area of operation.

5 Conclusion

The study has effectively empirically demonstrated that a combination of Multi-objective Fox Optimization Algorithm and Adaptive Kalman Filter based solution provides a very effective and tested shows evidence of improvement of autonomous UAV guidance functioning under the dynamic and uncertain conditions. The presented framework overcomes the key drawbacks of every effort towards path efficiency, collision transgression, and reliable localization by merging flexibility of adaptive sensor fusion and multi-objective global optimization.The Adaptive Kalman Filter has strongly enhanced the accuracy of state estimation by adjusting process and measurement noise parameters dynamically so that the system can become insensitive to the uncertainties when a sensor is used and environmental disturbances. In the meantime, the Multi-objective Fox Optimization Algorithm was capable of finding a good compromise between competing goals, reducing the distance of a flight, saving energy, and maximizing safety margins, and it performs better and makes more stable flight paths than classic algorithms (e.g. A*, PSO, and GA).Performance assessment indicated that the suggested technique realized a higher accuracy (95.53%), precision (94.15%), recall (93.62%), and F1-score (93.87%) in comparison to the current techniques, and the statistical t-tests proved that the gains were quite tremendous ($p < 0.001$). The decreased variances in the results also showed the strength and stability of the system to various testing situations.All in all, the solution offered has high potential of application in the real world in disaster relief and search-and-rescue missions, logistics, surveillance, and environmental surveillance. The ability to work in real-time, perform trade-off between multiple objectives and ensure safety in its operation qualifies it as a next generation UAV autonomy framework.Future research directions are to apply this to multi-UAV coordination, use of deep reinforcement learning to adapt the policy and integration of edge AI to allow onboard decision-making in low latency, leading to completely autonomous aerial mission systems.

Declaration

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

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

Competing interests: here are no have no conflicts of interest to declare.

Authors' contributions (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript

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Hybrid Models for Forecasting Interior Lighting Energy Consumption Using Support Vector Regression, CatBoost, and Chaos Game Optimization

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In the scientific community, forecasting building energy use has emerged as a key strategy for improving energy efficiency in recent years. A significant portion of electricity is used for building lighting. However, because there are so many variables that affect lighting energy usage, it is still difficult to predict with any degree of accuracy. Given the need and significance of forecasting building energy consumption, this study attempted to forecast building interior lighting energy using machine learning (ML) techniques. The primary ML techniques employed in this work are the Chaos Game Optimization (CGO) algorithm in conjunction with support vector regression (SVR) and categorical boosting (CatBoost). These algorithms were integrated into hybrid frameworks (SVR-CGO and CatBoost-CGO) in order to optimize hyperparameters and enhance predictive performance. The aim of this integration is to create hybrid models that optimize the hyperparameters of the main algorithms. The case study's findings demonstrated that the suggested approach had a suitable and acceptable level of accuracy and that the hybrid models it suggested could accurately estimate a building's interior lighting energy values. Specifically, the models achieved R^2 values above 0.99 across most energy categories, with the CatBoost-CGO hybrid yielding the lowest error values (RMSE = 39.23, MAE = 14.87, MAPE = 0.0144 for label A) and the SVR-CGO hybrid performing better in categories B, C, and E (R^2 up to 0.9999 and RMSE as low as 1.93). The results showed that the Catboost-CGO hybrid model is more accurate because, according to the test dataset, it has relatively higher evaluation index values in the energy labels A, D, F, and G. However, based on other energy categories, i.e., energy categories B, C, and E, the evaluation indices show that the SVR-CGO hybrid model performed better. Overall, based on the research findings, the Catboost-HGS hybrid is recommended for predicting the energy consumption of interior lighting in buildings. These results demonstrate that the proposed hybrid models can provide reliable predictions to support energy-efficient building design and operational strategies.

Povzetek: Študija napoveduje porabo notranje razsvetljave z hibridi SVR-CGO in CatBoost-CGO, kjer CGO uglašuje hiperparametre za natančnejše napovedi, uporabne pri energetsko učinkovitem načrtovanju in obratovanju stavb.

1 Introduction

Energy consumption forecasting has become crucial in the modern era because of the high cost of fossil fuels [1]. Due to urbanization and social growth, the construction industry consumes the most energy of all the consuming sectors, particularly in residential structures. The temperature and environment at the building site, the materials chosen for the walls and outer shell, the architectural and structural design, and the facility type are all factors that affect how much energy a structure uses. Therefore, it is essential to optimally prevent the wastage of facilities and take steps to save and increase the efficiency of the building. Big data, powerful and affordable computing resources, and advanced ML algorithms have been researched in the building sector inthe past decades and have shown their potential to increase building efficiency [2], [3]. Buildings still rely mostly on non-renewable fossil fuels for their energy needs. However, the building sector also has the most room to improve energy efficiency. Energy security and the possibility that the buildup of greenhouse gases may have negative impacts are growing worries due to the rising demand for fossil fuels and the uncertainty surrounding their future supply. In light of the current global environment, it is imperative to identify strategies for load reduction, productivity enhancement, and the integration of renewable energy sources across all facility types [4], [5], [6]. Because of the growing need for energy brought on by the world's population expansion, energy businesses continue to face challenges in forecasting energy consumption. According to scientists, if energy usage is not reduced, scarcity might occur within a few years [2]. The design of energy-efficient buildings and the

optimization of energy consumption in existing structures are the two primary areas in which approaches and tactics to lower building energy consumption may be examined. Choosing the best tactics and solutions to lower building energy consumption has become increasingly crucial as a result of the complexity and implementation costs that have grown with the introduction of new technologies [7], [8].

Over the past 20 years, a variety of techniques have been employed to predict building energy consumption. These methods may be divided into three groups: AI, statistical, and engineering methods [9], [10]. A subset of AI, ML models are computer models that can mimic human behavior to accomplish a variety of tasks in a wide range of scientific domains [11]. The main advantage of ML is that by identifying the underlying relationship between the desired input and output variables, its models can predict the correct response for a system without the need for human interaction. For the learning process, these algorithms typically require a significant volume of data and a comparatively limited number of input characteristics [12], [13],[14]. Many ML approaches have been introduced in the building industry in recent years to estimate lighting, HVAC loads, energy consumption, and performance under various scenarios. Based on the components of their predictions, AI-based prediction models may be categorized into three types: Personal, group, and hybrid [15], [16]. Individual predictive models use a learning algorithm. These models include artificial neural networks, classification trees, SVM, SVR, etc [17]. Ensemble models consist of several predictive models that are specified in a way that determines the output data. Ensemble methods include Voting and Bagging. These methods have attracted the attention of the ML and soft computing communities in recent years. Today, ensemble learning methods are widely used due to their favorable performance in forecasting [18]. Hybrid models include: single-phase models, multi-phase models, and proposed models. These models combine two or more ML techniques. These models are more resistant than the others and provide better prediction accuracy. Based on the studies, a comprehensive comparison shows that the combined model of individual and ensemble models is more accurate [19].

The electrical energy used in buildings can be divided into two parts: lighting and building electrical equipment, such as coolers and refrigerators. According to reports, lighting in homes, businesses, and other establishments accounts for a sizeable portion of the overall power usage. Hence, much work has been done to reduce the energy usage of lighting systems in homes and businesses by looking into energy-efficient lighting systems, such as new light sources, lamps, and lights, and combining them with daylighting [20], [21]. In particular, studies have been done to prevent excessive glare, reduce indoor cooling loads, and maximize lighting energy savings in order to use daylight appropriately and efficiently. This is because using daylight has been shown to have positive psychological and physiological effects on humans [22]. The classification of electrical energy consumption for building electrical equipment is known from the energy label of each equipment. It is possible to determine the classification of electrical energy consumption in the lighting sector and use a weighted average of the energy consumption elements to determine the classification of the building's total electrical energy consumption. Determining a building's lighting consumption category may be challenging as it relies on both the building's construction and surrounding conditions. As a result, it cannot be determined solely from the energy label, but there is no such dependence on other electrical equipment in the building, and the energy label of the equipment is easily sufficient [13], [23]. As a result, it is very challenging to estimate the quantity of lighting energy consumption in the structure with precision owing to the effect of several elements [24].

A variety of studies pertaining to the study topic are examined in the sections that follow. Amasyali and El-Gohary (2016) used SVM to forecast how much energy building lights will use. The suggested approach is sufficiently accurate to forecast lighting energy use, according to a case study conducted on a Philadelphia office building [25]. A multi-objective approach for predicting building energy efficiency was proposed by Yang et al. (2020). They accomplished this by introducing a hybrid optimizer based on ML [26], which addressed the non-linear multi-objective optimization issue. A hybrid model based on short-term memory networks, named eDemand, was presented by Somu et al. (2020) to investigate the problem of predicting building energy consumption. In the proposed method, the improved version of SCOA was used to optimize LSTM hyperparameters [27]. Jallal et al. (2020) forecasted energy usage time series using a neural-fuzzy inference system that was improved using an optimizer. In the proposed method, the autoregression process was used to generate inputs [28]. Liu and colleagues (2021) attempted to improve the building's energy efficiency by employing a hybrid model that was based on random forest. The results demonstrate that the RF model offers a number of benefits when it comes to forecasting building energy usage [29]. Li and Yao (2021) predicted the energy consumption for building stock's heating and cooling using a hybrid model. The accuracy evaluation indices confirmed the proposed method [30]. Rough set theory and DL techniques were used in Lei et al.'s (2021) model to forecast building energy usage. DL was used to extract the characteristics of building energy consumption data, and the proposed method used rough set theory to minimize the factors impacting building energy consumption [31]. In order to forecast hourly energy consumption based on four patterns, Dong et al. (2021) employed group learning algorithms. Patterns of energy use were categorized using decision tree analysis [32]. Alraddadi and Othman (2022) introduced a model that uses ML approaches to forecast power usage. The results showed that the proposed long-term short-term memory (LSTM) based method was very accurate [33]. Estimating the building's energy consumption is crucial since, according to the literature research, it is one of the largest energy users when compared to other economic sectors. The literature review also showed that ML and DL

techniques are well-liked methods for predicting energy use, and several investigations have shown their exceptional accuracy. According to the literature review, a number of models and methods have been created thus far to predict how much energy buildings would need; each has certain advantages and traits and has been used depending on the situation. However, all of the studies have demonstrated how useful and successful ML-based methods are in predicting energy use. In order to produce a model for forecasting building energy usage, two optimized ML algorithms—SVR and CatBoost—were used in this work. While prior studies have combined machine learning algorithms with metaheuristic optimization for hyperparameter tuning, most have focused on broader energy consumption or heating and cooling loads. To the best of our knowledge, no study has specifically targeted interior lighting energy consumption across diverse BER categories using such hybrid approaches. Furthermore, this study investigates two distinct hybridizations (SVR-CGO and CatBoost-CGO), offering a comparative perspective on their strengths and limitations in handling heterogeneous building energy classes. Here are some references to the remainder of the paper: The study methodology, including the introduction of algorithms, was described in Section 2. Section 3 displayed the study dataset. The study's findings were reported in Section 4. Lastly, the conclusion is covered in Section 5.

2 Methodology

The goal of this research is to develop a hybrid ML model that can be used to forecast the energy consumption of interior lighting in various building types with various energy labels (A, B, C, D, E, F, and G). "Interior lighting energy," expressed in kWh/m^2/year, is an output variable, whereas the other eighteen attributes are input variables. This work used SVR and CatBoost algorithms to predict the energy usage of indoor lighting. In decision trees, CatBoost is simply a specific type of gradient boosting that can handle ordered and classified information. SVR is another ML method for applications involving regression. SVR is an extension of SVM for regression problems. The next section goes into further depth about these two tactics. To improve prediction accuracy, the algorithms were combined with the meta-heuristic algorithm CGO to develop two hybrid models: CatBoost-CGO and SVR-CGO. The purpose of these two hybrid models is to optimize and modify each of the main algorithms' hyperparameters. The K-fold cross-validation approach was also applied, with a value of k = 5, to assess the models' performance. Partition the dataset into K equal-volume parts to start the K-fold cross-validation procedure. The first fold is considered test data, while the subsequent (K-1) folds are considered training data. The training set of data is then used to train the model. The accuracy of the model is then confirmed using the test data. Using different folds as test data for each iteration, compared to the ones that were initially chosen, this cycle is repeated K times. Each fold is, therefore, chosen exactly once to serve as training and test data by using the strategy K times. The assessment process ends with K repetitions of the procedure and an average of the outcomes. By dividing the output variables into several BER categories utilizing a case study and additional statistical evaluation indices, the accuracy of the proposed approaches was finally investigated. In this study, four statistical evaluation indices were adopted to assess the accuracy of the proposed hybrid models: the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). R^2 measures the proportion of the variance in the dependent variable that is predictable from the independent variables, indicating the goodness of fit. RMSE reflects the square root of the average squared differences between the predicted and observed values, thus emphasizing larger errors. MAE computes the average absolute differences between predictions and observations, providing an easily interpretable measure of average error. MAPE expresses prediction errors as a percentage, allowing for scale-independent comparisons. These indices were calculated according to the mathematical formulas provided in Table 1 and were employed to evaluate both the training and testing performance of the models across different building energy labels [34], [35], [36], [37]: Observation means ($\bar{o}$), ith observed value (o_i), ith estimated value ($\hat{o}_i$), and the number of observations (n) are all shown in Table 1.

Table 1: Indexes of statistical evaluation

Statistics	*Name*	*Equation*
R^2	Coefficient of Determination	$R^2 = 1 - \frac{\sum_{i=1}^{n}(o_i - \hat{o}_i)^2}{\sum_{i=1}^{n}(o_i - \bar{o})^2}$
RMSE	Root Mean Square Error	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(o_i - \hat{o}_i)^2}{n}}$
MAPE	Mean Absolute Percentage Error	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\|\frac{o_i - \hat{o}_i}{o_i}\right\|$
MAE	Mean Absolute Error	$MAE = \frac{\sum_{i=1}^{n}\|o_i - \hat{o}_i\|}{n}$

2.1 Categorical boosting (CatBoost)

The terms "Category" and "Boosting" refer to the gradient boosting method known as "CatBoost," which is based on decision trees. Additionally, one supervised ML technique for prediction and classification issues is called CatBoost. Researchers and engineers at Yandex created CatBoost in 2017 [38]. By default, this approach creates 1000 trees; however, by lowering the number of iterations, training may be accelerated. As the number of repeats decreases, the learning rate increases. This algorithm's implementation of symmetric trees is one of its characteristics; this feature not only shortens the prediction time but also greatly boosts the potential of prediction during the testing phase [39]. Reducing overfitting is another benefit of building symmetric trees in CatBoost. Compared to previous algorithms, CatBoost can learn and predict 13–16 times faster because it leverages networked graphics processors. The main feature of CatBoost is its remarkable stability, which is demonstrated by its capacity to function on a variety of data sources and its lack of need for a significant quantity of training data, in contrast to other ML models. Additionally, internal handling for missing data is included [40].

For the CatBoost model, the maximum tree depth was explored in the range of 6–10, while the learning rate was varied between 0.01 and 0.1. The number of iterations was capped at 1000, with early stopping applied to prevent overfitting. CatBoost's built-in handling of categorical variables and missing values was leveraged, which reduced the need for extensive preprocessing. All hyperparameters were systematically optimized using the CGO algorithm to identify the configuration yielding the best predictive accuracy.

2.2 Support vector regression (*SVR*)

The ML-based *SVR* approach is used to solve regression and classification issues. SVR extends SVM to address regression difficulties. In a high-dimensional feature space, SVR seeks to identify a hyperplane that most accurately depicts the target variable's maximum variance. A collection of input-output training data is provided to SVR, with each data point having a set of input attributes and an output value that corresponds to them. A kernel function is used to convert the input characteristics into a higher-dimensional space. SVR may therefore be able to capture more intricate relationships between characteristics and the target variable. The aim of SVR is to find the hyperplane with the largest margin from the training data points. The margin shows the maximum separation between the nearest data points and the cloud plane. SVR seeks to minimize margin violations while cramming as many data points as feasible into the margins. Data points that are close to or depart from the mean are known as support vectors [41], [42], [43]. Using a loss function, SVR penalizes the variation between the expected and actual values. The loss function that is most frequently employed in SVR is the epsilon-insensitive loss function. Errors outside the margin are penalized, whereas errors inside the margin are granted a certain tolerance (epsilon). The SVR technique finds the optimal hyperplane that maximizes margin and minimizes error in the transformed feature space. During the training phase, constrained optimization issues must be addressed. Using the appropriate metrics, the SVR model can be assessed after training. The trained SVR may predict new, unknown data by translating the input characteristics using the learned mapping and utilizing the regression function. SVR is a useful technique for regression problems, especially when managing complex, non-linear relationships between data and objectives. In many disciplines, including engineering, economics, and finance, where it is often used, the ability to predict continuous values is essential [44], [45], [46].

In this study, the SVR model was implemented using a radial basis function (RBF) kernel, which has been widely recognized for its ability to capture nonlinear relationships in energy consumption data. The penalty parameter (C) was set within the range [1, 100] based on cross-validation, while the epsilon (ε) value was tuned between 0.01 and 0.1 to balance model tolerance against prediction error. The kernel coefficient (γ) was also optimized via CGO to enhance generalization performance.

2.3 Chaos game optimization (CGO)

The chaotic game and fractal geometry are two sources of inspiration for the CGO meta-heuristic optimization method. Zhang first suggested it as a population-based optimization technique in 1997. Using a set of rules, the chaos game is a mathematical technique that repeatedly places points inside a geometric form to create fractal patterns. This idea is modified in CGO to address optimization issues. In the search space of the optimization problem, this method first creates a random initial population of solutions. The objective function is used to determine if a solution is acceptable to the community. The algorithm uses a randomly selected solution from the population as a reference point. A new solution is then computed by squaring the weighted average of the chosen solution and the reference point. A specific number of repetitions of this process is required to generate a new set of solutions. The optimal solution is chosen after the acceptability of the collection of new solutions is assessed using the objective function. The selection process can be based on criteria such as fitness ranking or elitism. Until the termination criteria are met, these activities continue. Reaching an appropriate solution, the utmost number of iterations, or other preset parameters might constitute these criteria. The concept behind CGO is that by combining randomness with direction from the reference point, the chaotic game operation aids in searching the search space and locating viable solutions. CGO seeks to converge on an ideal solution by repeatedly updating the population and choosing the best options [47], [48], [49].

CGO was selected in this study over other metaheuristics (e.g., Particle Swarm Optimization, Genetic Algorithms) due to its strong balance between exploration and exploitation in high-dimensional search

spaces. Unlike many algorithms that risk premature convergence, CGO employs chaotic mapping to diversify the search process, thereby reducing the likelihood of being trapped in local minima. This property makes CGO particularly suitable for the complex; nonlinear optimization tasks associated with tuning the hyperparameters of SVR and CatBoost.

3 Dataset description

The energy stock of Irish residential structures is the main topic of the data utilized in this study. EPCs, sometimes known as BER certificates locally, are governed by the $SEAI$. The main purpose of this data is to compile statistics about Irish residential structures. In addition to more than 200 architectural criteria, the study concentrated on the Irish city of Dublin and the Dublin EPC dataset, which included 339,494 of 624,758 residential structures—the largest percentage of all Irish buildings. The BER in the Irish EPC dataset is determined by the projected yearly energy consumption per square meter. This rating uses a graded system to score the building's energy performance from A1 to G. The statistics show that detached and semi-detached houses are the most prevalent construction types. The Irish EPC-BER chart, which displays the proportion of total EPC vs. non-EPC residential developments, is used to assess building energy efficiency (Fig. 1).

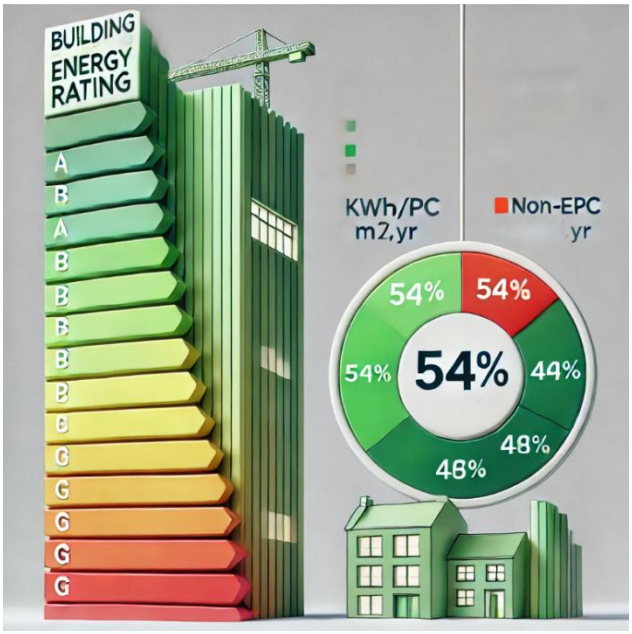

Figure 1: Building energy performance is assessed using the Irish EPC-BER chart.

Fig. 2 shows the geometric models of many building types, including detached, semi-detached, terraced, and cottages. "Interior Lighting Energy" is one of the output variables, and there are eighteen input variables. U-values for HVAC systems, as well as different aspects of the building fabric, doors, windows, roofs, floors, and other components, are included in this dataset. Measurements of the energy demands for solar systems, appliances, lights, heating, and hot water are also included.

Figure 2: The geometric model of different residential building types.

In terms of preprocessing, missing values were handled through CatBoost's internal mechanism, which reduces the need for imputation. Outliers were identified and removed using interquartile range (IQR) filtering. Furthermore, all continuous input variables were normalized to ensure comparable scales across attributes and to improve training stability.

The models were implemented in Python 3.9 using scikit-learn (v1.1) for SVR and CatBoost (v1.0.6) for gradient boosting. The CGO optimizer was coded in Python and integrated into the training pipeline. All experiments were executed on a workstation equipped with an Intel Core i7 processor, 32 GB of RAM, and Windows 10 OS.

4 Results

This section discusses how well the suggested hybrid models forecast a building's interior lighting energy. The observation-prediction scatter plot for the two suggested hybrid models, categorized by building energy category (A to G) and dataset type (train versus test), is displayed in Fig. 3. For every dataset, the R-squared (R^2) index is also displayed. This image shows that both hybrid models have equal R^2 values in energy labels B, C, and E based on the training dataset. They have received training with a comparable level of accuracy. However, based on energy label A, the SVR-CGO hybrid model has a higher R^2 values with R^2 value of 0.999. However, based on other energy labels, namely D, F, and G, the SVR-CGO hybrid model has higher R^2 values , and thus it has been trained more accurately.

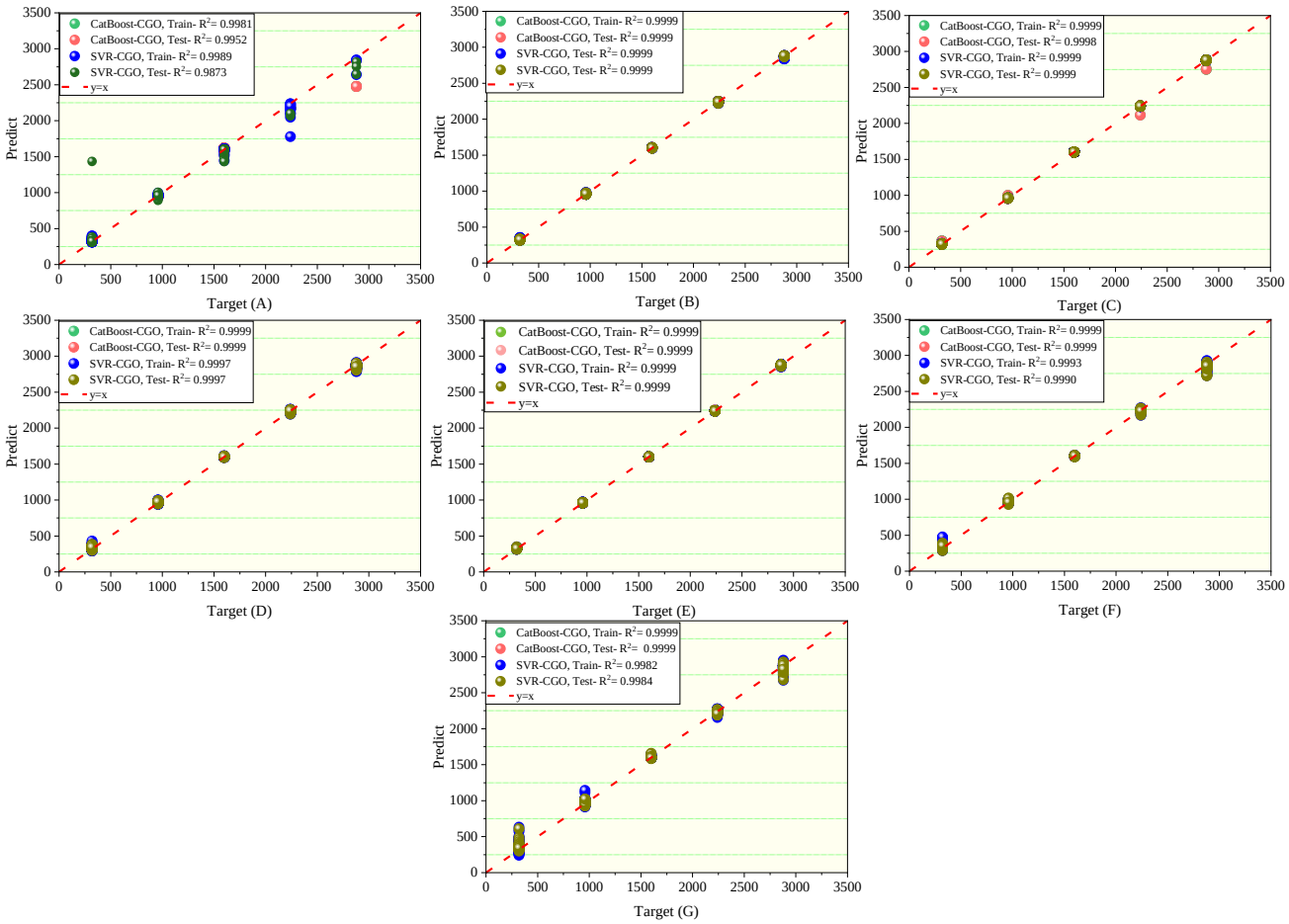

Figure 3: The observation-prediction scatter plot.

Based on the test dataset, both hybrid models have equal R^2 values and thus have similar accuracy in energy labels B, C, and E. However, based on other residual energy labels, namely A, D, F, and G, the SVR-CGO hybrid model has higher R^2 values and, thus, more accuracy. Consequently, the R^2 index suggests that the SVR-CGO hybrid model outperforms the Catboost-CGO hybrid model. Tables 2 and 3 present the statistical evaluation index values for the SVR-HGS and Catboost-HGS hybrid models' test and train datasets.

Table 2: The Catboost-CGO hybrid's statistical assessment indicators.

Rating Energy	R^2	RMSE	MAE	MAPE
	Train			
A	0.9982	22.9277	12.2543	0.0139
B	1	4.5839	3.9605	0.0035
C	0.9999	7.1912	2.1621	0.0028
D	1	3.07	2.9666	0.0035
E	1	5.2954	4.9654	0.0061
F	1	5.6509	5.4537	0.0056
G	1	4.337	4.1864	0.005
	Test			
A	0.9952	39.2294	14.8728	0.0144
B	0.9999	4.6132	4.0292	0.0035
C	0.9985	9.4191	2.4726	0.0028
D	0.9999	3.0713	2.9716	0.0035
E	0.9999	5.278	4.9366	0.0066
F	0.9999	5.6509	5.6788	0.005
G	0.9999	4.2701	4.116	0.005

Table 3: The statistical evaluation indices related to the SVR-CGO hybrid model.

Rating Energy	R^2	RMSE	MAE	MAPE
	Train			
A	0.999	17.8314	4.2167	0.006
B	1	5.4174	2.4567	0.0034
C	0.9999	1.8703	1.1061	0.0016
D	0.9998	15.7613	9.8856	0.0135
E	1	4.6873	2.8568	0.0038
F	0.9994	27.5133	16.5491	0.0234
G	0.9983	44.2861	27.2802	0.0395
	Test			
A	0.9874	63.2576	9.8868	0.0174
B	0.9999	3.4386	2.0458	0.0030
C	0.9999	1.9343	1.183	0.0017
D	0.9998	16.0151	10.4278	0.0144
E	0.9999	5.2323	3.1587	0.0048
F	0.999	33.7928	21.12	0.0187
G	0.9985	43.2874	27.9513	0.0375

To make comparing hybrid models easier, Fig. 4 shows the plot of the evaluation indices separately by dataset type (train or test) and building energy category (A to G). According to Fig. 4 and Tables 2 and 3, it can be found that based on the training dataset, in the energy labels D, F, and G, the Catboost-CGO hybrid model has relatively higher values of evaluation indices than the SVR-CGO hybrid model. Therefore, in these energy labels, the Catboost-CGO hybrid model can be expected to be trained more accurately. However, based on other energy categories, i.e., energy categories A, B, C, and E, the SVR-CGO hybrid model has better performance and has been trained more accurately.

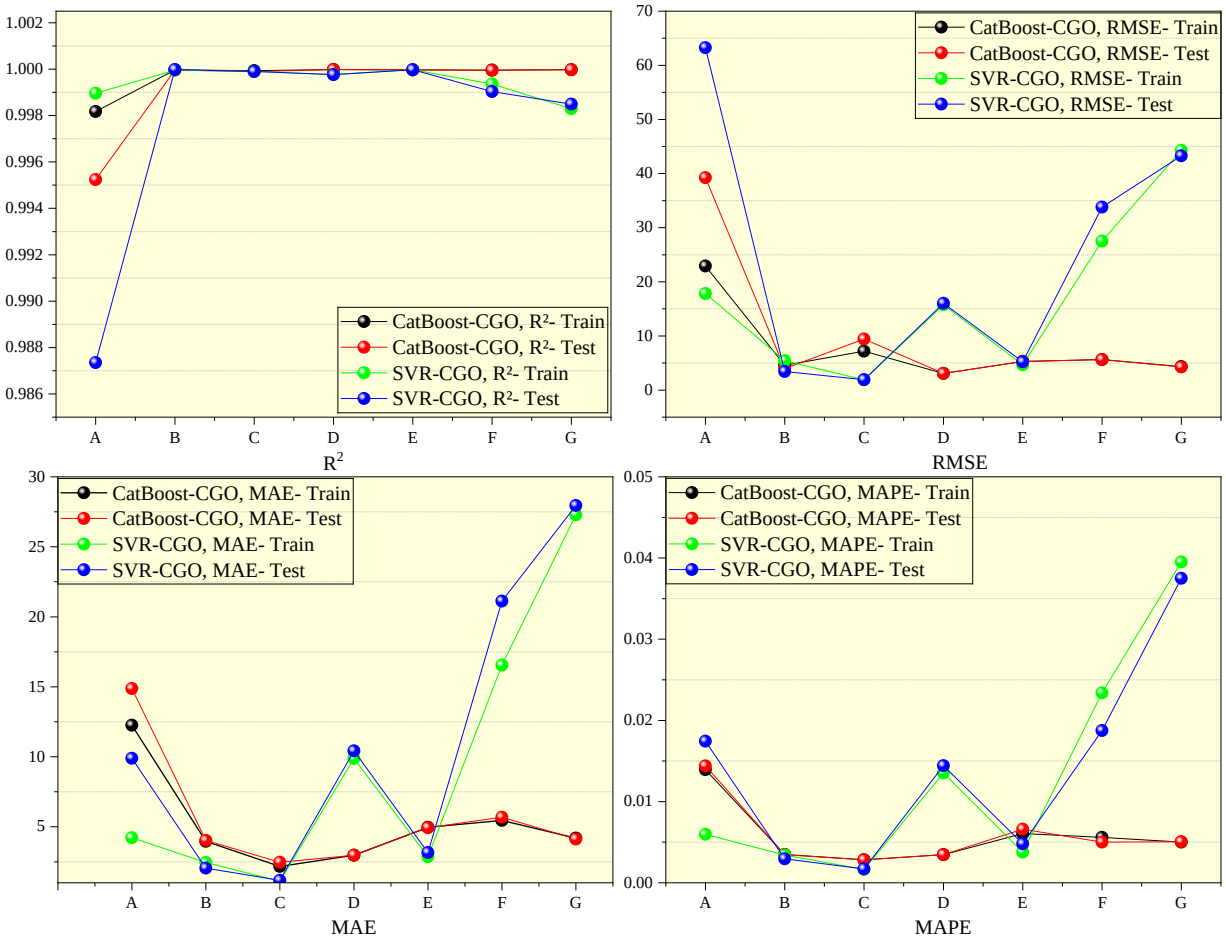

Figure 4: Hybrid model performance according to the assessment indices.

To evaluate the statistical significance of performance differences between CatBoost-CGO and SVR-CGO hybrid models, Wilcoxon signed-rank tests were conducted on all evaluation metrics across training and test datasets. This non-parametric test was selected due to the small sample size (n = 7 energy ratings) and to avoid normality assumptions. The analysis employed paired comparisons between models across energy rating categories A through G, with a significance level of $\alpha = 0.05$. Results demonstrate clear statistical superiority of the CatBoost-CGO approach, achieving statistically significant better performance in 7 out of 8 comparisons (87.5%). For training data, CatBoost-CGO showed significant improvements in all error metrics (RMSE, MAE, MAPE) with p = 0.0156, while R^2 showed no significant difference (p = 0.109). Test set results reinforced CatBoost-CGO superiority across all metrics, including significantly better R^2 performance (p = 0.047) and consistent error reduction (p = 0.0156 for all error metrics). The low W statistics (0.0-9.0) indicate consistent outperformance across energy rating categories rather than isolated improvements. Mean error reductions of 8.59 RMSE units (training) and 13.54 units (testing) demonstrate substantial practical improvements. These findings provide strong statistical evidence supporting CatBoost-CGO's effectiveness for building energy consumption modeling, validating both superior accuracy and generalization capabilities compared to the SVR-CGO alternative.

Table 4: Wilcoxon Signed-Rank Test Result, CatBoost-CGO vs SVR-CGO Model Comparison

Dataset	Metric	CatBoost Mean	SVR Mean	Mean Difference	W Statistic	p-value	Significant?	Better Model
Train	R^2	0.9997	0.9995	0.0002	9.0	0.109375	No	No difference

Dataset	Metric	CatBoost Mean	SVR Mean	Mean Difference	W Statistic	p-value	Significant?	Better Model
Train	RMSE	8.1466	16.7383	-8.5917	0.0	0.015625*	**Yes**	**CatBoost-CGO**
Train	MAE	5.1344	9.2068	-4.0724	0.0	0.015625*	**Yes**	**CatBoost-CGO**
Train	MAPE	0.0058	0.0146	-0.0088	0.0	0.015625*	**Yes**	**CatBoost-CGO**
Test	R^2	0.9991	0.9965	0.0026	3.0	0.046875*	**Yes**	**CatBoost-CGO**
Test	RMSE	10.3400	23.8800	-13.5400	0.0	0.015625*	**Yes**	**CatBoost-CGO**
Test	MAE	5.7265	10.8326	-5.1061	0.0	0.015625*	**Yes**	**CatBoost-CGO**
Test	MAPE	0.0058	0.0164	-0.0106	0.0	0.015625*	**Yes**	**CatBoost-CGO**

The test dataset indicates that in energy labels A, D, F, and G, the $Catboost$-CGO hybrid performs better than the SVR-CGO hybrid. Therefore, in these energy labels, it can be expected that the Catboost-CGO hybrid model will be more accurate in predicting the interior lighting energy of buildings. However, based on other energy categories, i.e., energy categories B, C, and E, the evaluation indices show that the SVR-CGO hybrid model has a better performance and, therefore, more accurately predicts the amount of lighting energy.

To provide a broader perspective, the performance of the proposed hybrid models was also contrasted with representative results from existing state-of-the-art methods reported in the literature. For example, Amasyali and El-Gohary (2016) [25] employed a traditional SVM model to predict lighting energy use, achieving R^2 values in the range of 0.92–0.95. Similarly, Somu et al. (2020) [27] introduced an LSTM-based hybrid approach, which demonstrated improved accuracy compared to conventional statistical models, though still limited by computational costs. Random Forest-based hybrid models, as reported by Liu et al. (2021) [29], achieved R^2 values around 0.97–0.98 in forecasting building energy consumption. In comparison, the proposed SVR-CGO and CatBoost-CGO models consistently attained R^2 values above 0.99 across most building energy labels, as well as significantly lower RMSE and MAE values. This evidence suggests that the proposed hybrid framework offers measurable improvements over classical ML models and is highly competitive with advanced deep learning-based approaches.

Box plots showing the error values of the test and train datasets' respective hybrid models within 1.5IQR are provided in Fig. 5. The SVR-CGO, according to the test dataset, has shorter outliers at energy labels A, B, C, and E and a smaller error range within 1.5IQR, as this image illustrates. The SVR-CGO performs better than the $CatBoost$-CGO, as seen by this problem, which displays less error dispersion and, in fact, lower standard deviation values. However, according to the test dataset and additional energy labels (D, F, and G), the Catboost-CGO hybrid model has a smaller error range and, hence, a less dispersed error distribution. Consequently, it is reasonable to anticipate that the Catboost-CGO hybrid model will perform better in these energy labels and have a smaller error standard deviation.

For both hybrid models, Fig. 6 shows the normal distribution curves and error value scatter plots fitted to the error frequency histograms. Scatter plots show that when all energy labels are taken into account, the SVR-CGO hybrid model's fluctuation amplitude of error changes is greater than that of the Catboost-CGO hybrid. Furthermore, the distribution curves demonstrate that the Catboost-CGO hybrid outperforms the SVR-CGO hybrid model in terms of performance and error values, as seen by its shorter outliers and lowest enclosed area. The results also showed that compared to other energy labels, the Catboost-CGO hybrid model had a larger fluctuation amplitude of error variations in the B and C labels.

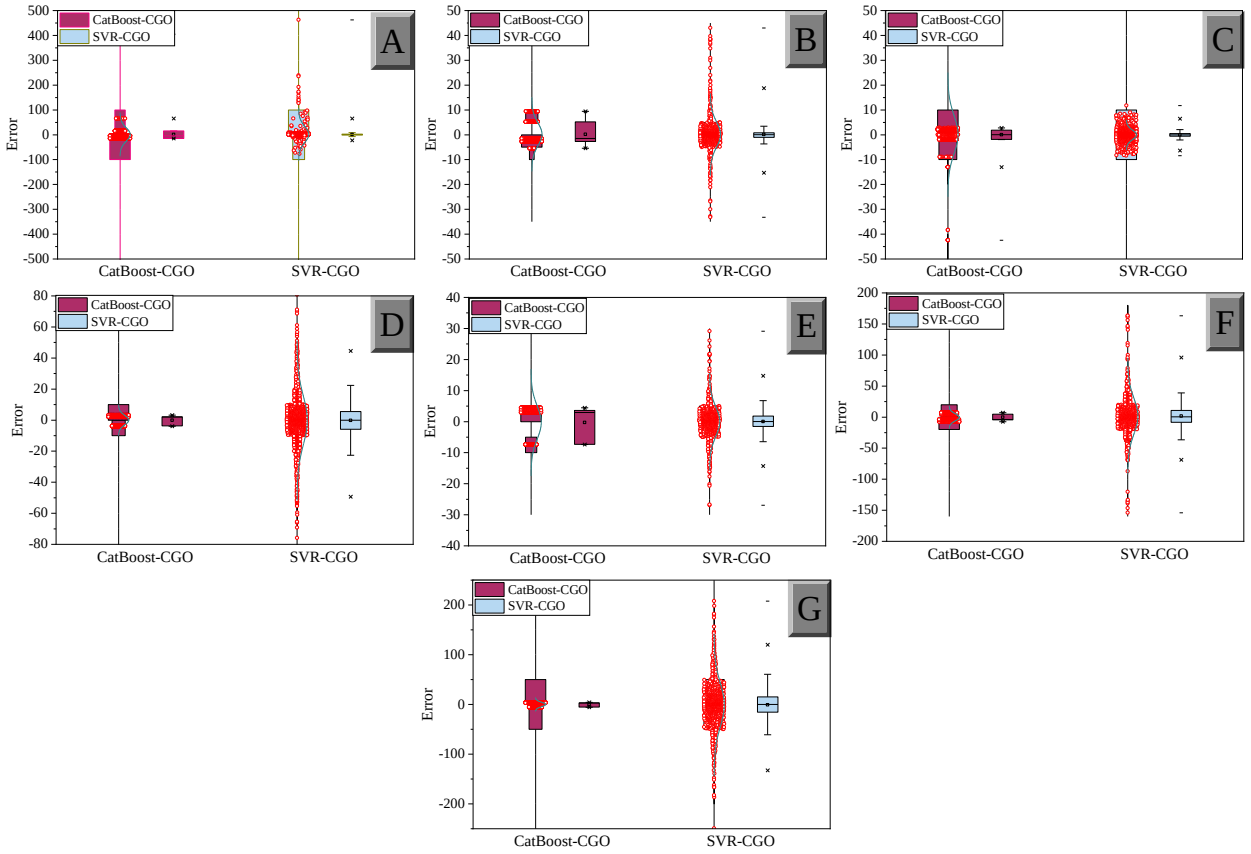

Figure 5: Statistical distribution of model errors illustrated through box plots.

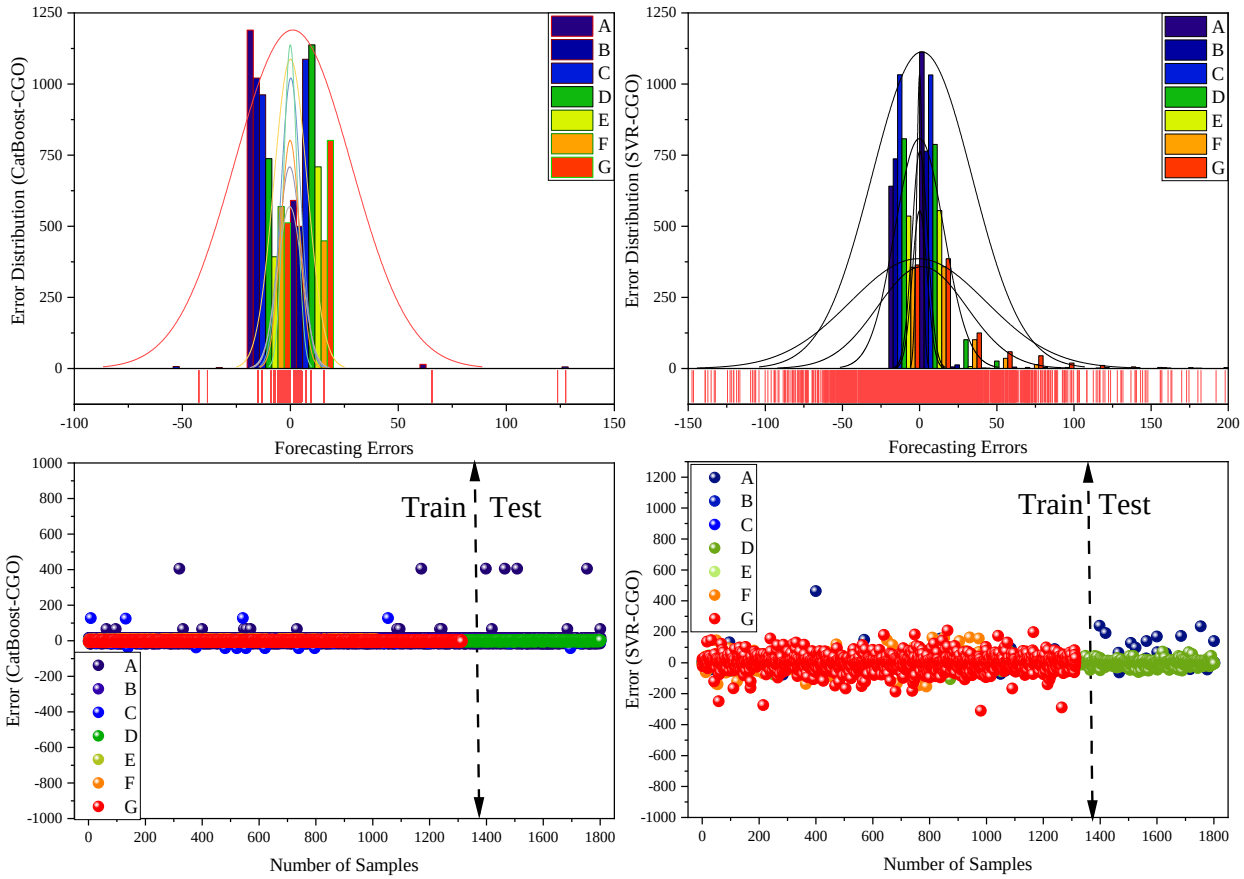

Figure 6: Comparison of the error values of models.

Each hybrid model's convergence curves are shown in Fig. 7. The vertical axis of this graphic displays the logarithmic value of the convergence, which is derived from the equation Z= [0.3* RMSE + 0.4*MAPE + 0.3 MSE], while the horizontal axis displays the iteration number, which is restricted to 500. This figure suggests that the Catboost-CGO hybrid model generally has lower convergence values than the SVR-CGO hybrid model. The $Catboost$-CGO hybrid's convergence curves demonstrate that it has the greatest and lowest convergence values for energy labels F and C, respectively. In contrast, the SVR-CGO hybrid model has the greatest and lowest convergence values in energy labels G and E, respectively, according to the convergence curves.

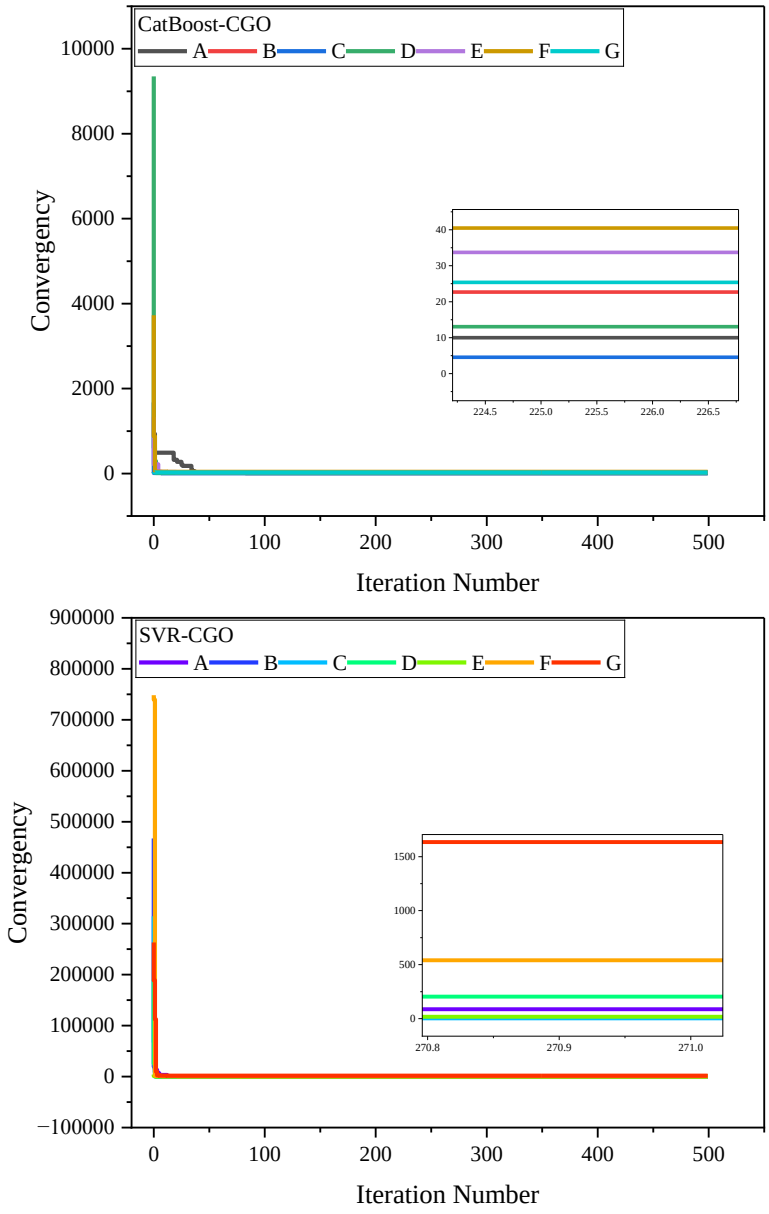

Figure 7: Curves of convergence for every hybrid model.

All of the models' run times across 500 iterations are displayed in Fig. 8. At the energy labels B, E, F, and G, the $Catboost$-CGO hybrid model has a longer overall run time than the SVR-CGO hybrid model, as seen in this figure. However, in other BERs, namely A, C, and D, the SVR-CGO hybrid model has a longer total run time than the SVR-CGO hybrid model.

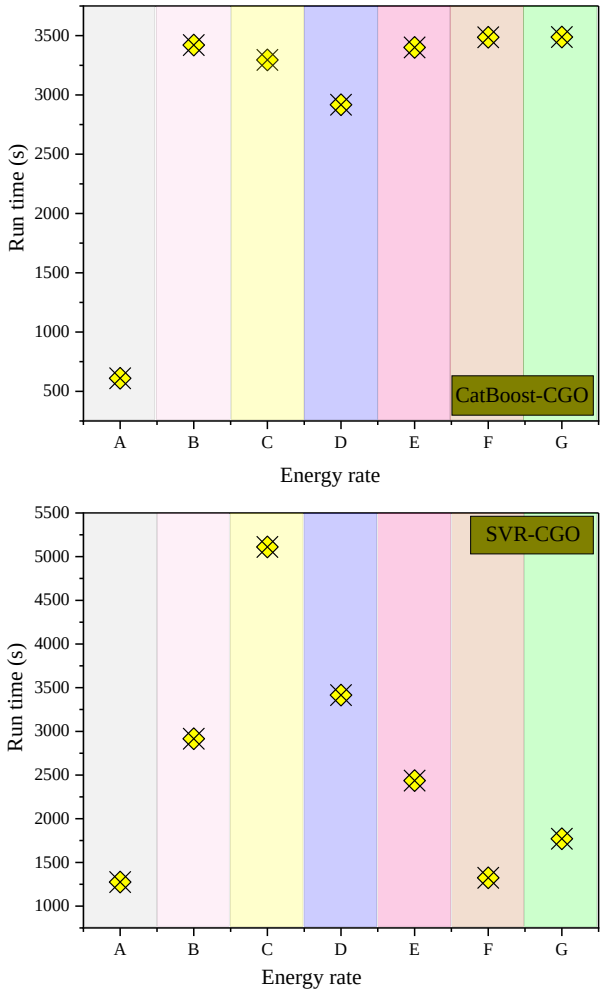

Figure 8: Comparison of total run time (s).

5 Conclusion

Building energy consumption is high, which has led to a number of environmental issues. Predicting a building's energy consumption is essentially promoted as a way to maximize energy efficiency and enhance decision-making. Therefore, ignoring the manner and amount of energy consumption and waste in buildings will result in irreparable damage. Reports indicate that a significant amount of the electricity used in buildings is for lighting. On the other hand, because so many factors affect lighting energy consumption, it is exceedingly difficult to predict the exact amount of energy consumption in the structure. Recent years have seen encouraging results from ML-based approaches in the field of energy demand prediction. In order to anticipate building interior illumination energy use, hybrid models based on ML were used. In this study, an accurate model was used. In this work, ML-based algorithms such as SVR and CatBoost were employed. The CGO approach was used to optimize and modify the primary algorithms' hyperparameters in order to enhance predictions.

A case study's findings demonstrated that the suggested approach had a suitable level of accuracy, and the suggested hybrid models could accurately forecast a building's interior lighting energy values. The results showed that based on the training dataset, in energy labels D, F, and G, the Catboost-CGO hybrid model has relatively higher values of evaluation indicators, and as a result, it is trained more accurately. Nevertheless, based on other energy categories, i.e., energy labels A, B, C, and E, the SVR-CGO hybrid model has better performance and has been trained more accurately. Based on the test dataset, in energy labels A, D, F, and G, the Catboost-CGO hybrid model has relatively higher evaluation index values , and as a result, it can anticipate a building's interior lighting energy with greater precision. However, according to other energy categories, i.e., energy labels B, C, and E, the evaluation indices show that the SVR-CGO hybrid model performed better. Additionally, the findings demonstrated that the Catboost-CGO hybrid model often has lower convergence values than the SVR-CGO hybrid model. The error analysis findings demonstrated that the SVR-CGO hybrid model's fluctuation amplitude of error changes is greater than that of the Catboost-CGO hybrid model, while taking into account all energy labels.

Also, the Catboost-CGO hybrid model leads to lower error values. Consequently, the Catboost-HGS hybrid is recommended to forecast the energy consumption of interior lighting in buildings based on the studies' findings.

In addition to demonstrating strong predictive accuracy, this work contributes novel insights by focusing on the underexplored problem of forecasting interior lighting energy across different BER categories. The application of CGO for hyperparameter optimization in both SVR and CatBoost frameworks, combined with a large-scale dataset of Irish residential buildings, offers methodological and domain-specific contributions not previously reported in the literature.

Beyond methodological contributions, the findings of this study also offer important practical implications. Accurate forecasting of interior lighting energy consumption can support architects and engineers in optimizing building design, for instance, by selecting construction materials, window-to-wall ratios, and lighting systems that minimize energy demand. For building operators, predictive models can be integrated into energy management systems to adjust lighting schedules, incorporate daylighting strategies, and reduce unnecessary consumption. At a policy level, reliable prediction tools can assist regulators in benchmarking building energy performance and setting more effective efficiency standards. By bridging advanced machine learning techniques with practical energy management, the proposed hybrid models provide a pathway toward more sustainable building operation and design practices.

List of Abbreviations

Abbreviation	Explanation	Abbreviation	Explanation
AI	Artificial Intelligence	n	The number of observations
BER	Building Energy Rating	$\hat{o}_i$	The i_{th} estimated value
CatBoost	Categorical Boosting	$\bar{o}$	The mean of the observations
CGO	Chaos Game Optimization	o_i	The i_{th} observed value
DL	Deep Learning	*SEAI*	Sustainable Energy Authority of Ireland
EPC	Energy Performance Certificate	*SVR*	Support Vector Regression
ML	Machine Learning	*SVM*	Support Vector Machine

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A Cascade GCN-LightGBM Framework for Abnormal Account Detection in Social Networks

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We propose a two-stage cascade pipeline that first extracts structural embeddings via a two-layer Graph Convolutional Network (GCN) and then fuses them with raw node attributes for LightGBM classification to detect abnormal accounts in social networks. Evaluated on three datasets—Weibo-social (1.26 M nodes, 18.4 M edges), NSL-KDD and IoT-23—the framework attains an F1 of 88.5 % on Weibo-social, outperforming single GCN (87.9 %) by 0.6 pp and XGBoost (85.5 %) by 3.0 pp while reducing training time from 247.8 min to 12.3 min (≈20× acceleration). Cross-domain transfers show consistent gains of 1.8–2.1 pp F1, confirming the synergy of topological and attribute features. Compared with existing behaviour-, content- or single-graph baselines, our approach simultaneously improves accuracy and efficiency without extra annotations.

Povzetek: Študija predstavi dvostopenjski postopek, ki z dvoslojno GCN izdela strukturne vgraditve in jih združi z atributi vozlišč za klasifikacijo z LightGBM, s čimer učinkovito zazna abnormalne račune z izkoriščanjem sinergije topoloških in vsebinskih značilk.

1 Introduction

As the digital network ecology continues to evolve, network account security [1] has become a key link in guarding users' rights and interests and network order. Among them, the hazards brought by abnormal accounts are becoming more and more prominent [2]: zombie accounts, with the help of automated scripts and batch operations, massively disseminate false information on social platforms, information communities and other scenarios, ranging from misleading public opinion and creating panic to maliciously attracting traffic and committing fraud, eroding the authenticity of network information in all aspects [3]; Sybil accounts (witch attack accounts) [4], however, infiltrate into normal user groups or launch phishing attacks to steal privacy by forging identities and constructing false social networks, or launching phishing attacks to steal privacy. Sybil accounts (witch attack accounts) [4], on the other hand, by forging identities, constructing false social networks, infiltrating into normal user groups, or launching phishing attacks to steal privacy [5], or engaging in illegal behaviors such as cyber water armies [6] and malicious bill-sweeping, are a serious threat to the security of users' information and the health of the platform's ecosystem.

However, the detection of anomalous accounts faces multiple challenges. On the one hand, the dynamic nature of features increases the difficulty of defence - attackers are well aware of the traditional detection system's reliance on static features (e.g., fixed login IPs, commonly used device identifiers). By dynamically changing proxy IPs and simulating multi-device environments, they can quickly bypass the detection rules and invalidate the defence system constructed based on static features [7, 8].

On the other hand, network complexity further blurs the boundary of anomalies - on crowdsourcing platforms, real people and machine accounts are mixed for task execution, short URL services hide the real jump links, and the diversified network behaviors of normal users (e.g., cross-platform sharing, temporary short-link usage) highly overlap with the malicious operations of anomalous accounts in terms of their surface features, making it difficult to differentiate them accurately. It is difficult to differentiate them accurately; in addition, the computational efficiency problem has become a bottleneck for large-scale detection - the traditional model requires full-volume data processing. In the face of hundreds of millions of accounts and terabytes of behavioural logs, it not only consumes a long time, but also results in a great waste of storage and arithmetic resources, making it difficult to adapt to the actual needs of real-time monitoring and rapid response [9]. These challenges are intertwined with each other, pushing academia and industry to explore more efficient and intelligent anomalous account detection solutions continuously.

In the field of anomalous account detection, existing methods have significant limitations. Behavioural or content-based models are highly dependent on manually designed features, such as manually refining the login frequency of an account, keywords of posted content, etc. [10-12]. However, the network environment is complex and volatile, new abnormal behavioural patterns keep emerging, and artificial features are difficult to cover these dynamic changes in time, resulting in a weak generalisation ability of the model when facing unseen scenarios, and unable to identify new abnormal accounts effectively. The single graph model in detection [13]

focuses on mining topological relationships between accounts, but ignores the account's attribute features, such as account registration time, historical reputation rating, etc. [14]. At the same time, unsupervised detection methods lack label guidance, it is difficult to distinguish between normal and abnormal account boundaries accurately, and in the face of complex confusion scenarios, the detection accuracy is difficult to meet the actual needs, prone to omission and misjudgment, and unable to guard network information security [15-17] reliably.

To address the pain points of anomalous account detection [18], this paper makes a series of key contributions: proposes the GCN-LightGBM cascade framework, which skillfully integrates topology and attribute features, breaks the limitations of a single model, and comprehensively captures the anomalous patterns of the account; designs a lightweight distributed training process, and reasonably splits the scheduling of the data and the tasks, to adapt to the massive data scenarios, and solve the resource wasting problem of the traditional model's full processing; also builds a test environment that simulates real dynamic changes, and experimentally verifies that the framework shows good robustness in terms of training time and resource consumption. A controlled testbed is constructed to emulate evolving attack patterns, validating the framework's robustness against concept drift, and highlights the efficiency advantage in terms of training time and resource consumption, thus building a solid performance foundation for actual deployment.

We treat abnormal-account detection as a binary classification task on an attributed social graph $G_t = (V_t, E_t, X_t)$ that evolves daily. The goal is to learn $f : V_t \to \{0,1\}$ maximising F1 while keeping training time below 15 min on a 32-core server. We hypothesise: H1 — adding GCN structural embeddings significantly lowers the 10-fold CV error of LightGBM (paired t-test, $p<0.01$); H2 — under equal GPU-hour budget, the two-stage cascade reaches minimum validation loss in fewer epochs than an end-to-end GNN of comparable width; H3 — the gains in H1–H2 remain statistically significant across a 30-day concept-drift window. Experiments in Section 4 quantify each hypothesis and identify boundary conditions.

Although the primary focus is abnormal-account detection in social networks, we additionally evaluate the proposed framework on two non-social graph datasets — NSL-KDD and IoT-23 — to assess its cross-domain structural generalisation capability. No social-media-specific features (e.g., tweets, avatars) are used in these auxiliary experiments.

2 Related theoretical knowledge

2.1 Graph convolutional networks (GCN)

In the technical system of anomalous account detection, Graph Convolutional Network (GCN) is one of the key theoretical supports. Its core principle revolves around the neighbour aggregation mechanism to achieve the updating of node representations, which is mathematically portrayed by equation (1) [19].

$$H^{(k+1)} = PReLU(\hat{A}\hat{D}^{-1}H^{(k)}W^{(k)} + XW_{dp}) \quad (1)$$

Here, $\hat{A}$ is the normalized adjacency matrix, which assumes the role of combing the node connection relationship in the network and eliminating the influence of the difference in connection strength, so that the node interactions in different connection density regions can be calculated under a unified scale; X represents the initial features, covering the account registration information, the basic behavioral trajectory and other raw data; and W_{dp} is the residual connection weight, which is the residual structure that can effectively alleviate the problem of the disappearance of the gradient during the training of the deep network With the help of the residual structure, it can effectively alleviate the problem of gradient disappearance during deep network training, guaranteeing the integrity of information transfer and the stability of model training. In terms of practical application value, GCN has the unique advantage of being able to capture abnormal subgraph structures accurately. In network account scenarios, such as densely connected Spam (spam) account clusters [20], these abnormal accounts often form tight subgraphs by interconnecting with each other. GCN can identify such abnormal aggregation patterns based on the aggregation and analysis of the graph structure from the massive account relationships, which can provide key structural features for the subsequent detection of abnormal accounts [21], and help build up a strong technical defence line for network information security. The interlayer propagation formula of GCN is equation (2).

$$H^{(l+1)} = \sigma\left(\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \quad (2)$$

where $H^{(l)}$ is the node feature matrix of layer l and $\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}$ is a symmetric normalization of the adjacency matrix [22] to avoid feature scale imbalance due to node degree differences. The computation of $\hat{A}$ is shown in Equation (3).

$$\hat{A} = A + I_N \quad (3)$$

where A is the original adjacency matrix and I_N is the unit matrix. The GCN encoder consists of two graph convolutional layers with 128-dimensional hidden units, PReLU activation, and a dropout rate of 0.3. Weights are initialised using Xavier uniform distribution.

2.2 Core algorithm and optimization mechanism of lightgbm model

LightGBM is an efficient integrated learning framework based on GBDT, developed by Microsoft as an open-

source project. It uses histogram optimization technology to discretize continuous features to build a histogram, significantly reducing the computation and memory consumption of the decision tree to find the optimal split point; through the gradient one-sided sampling, according to the sample gradient size ranking, retaining the high-gradient samples and randomly sampling the low-gradient samples, to improve the training efficiency without affecting the accuracy. In addition, optimization techniques such as leaf growth strategy and mutually exclusive feature bundling make it a powerful tool for data processing in large-scale data scenarios such as recommender systems and financial risk control [23].

In the field of integrated learning, LightGBM serves as an efficient implementation of gradient boosting decision trees (GBDT) based on gradient boosting. Its prediction model is constructed following the core logic of gradient boosting [24]. Specifically, the prediction model formalisation of LightGBM is defined in equation (4).

$$F_T(x) = f_0(x) + \sum_{t=1}^{T} \alpha_t f_t(x) \quad (4)$$

where $f_0(x)$ represents the initial weak learner, e.g., a single-layer decision tree, $f_t(x)$ represents the prediction function for the t-th tree, and α_t is the learning rate, which controls the contribution weight of each tree..

Calculation of splitting gain and histogram optimisation in the LightGBM model, the splitting gain of the decision tree is shown in equation (5).

$$Gain = \frac{1}{2}\left[\frac{(\sum_{i\in L} g_i)^2}{\sum_{i\in L} h_i + \lambda} + \frac{(\sum_{i\in R} g_i)^2}{\sum_{i\in R} h_i + \lambda} - \frac{(\sum_{i\in P} g_i)^2}{\sum_{i\in P} h_i + \lambda}\right] - \gamma \quad (5)$$

where g_i , h_i are the first-order and second-order gradients of the loss function of sample i. λ is the L2 regularization coefficient to prevent overfitting. γ is the split threshold to control the tree complexity. LightGBM designs two core strategies for efficient training [25]: gradient one-sided sampling is based on the difference of sample gradients, retaining key samples with large absolute gradient values and randomly discarding samples with small gradients, which accelerates training and maintains the accuracy at the same time; and mutual exclusion feature binding is used for mutually exclusion features with different non-zero values at the same time and combines them into a single feature to reduce the feature dimensions and reduce the computational overhead, which is suitable for high-dimensional and sparse data scenarios. This reduces the feature dimension and computational overhead, and is suitable for high-dimensional sparse data scenarios.

2.3 Fusion model

Under complex data scenarios and diversified task requirements, its own capacity boundaries often limit a single model, and the construction of fusion models has become a key path to break through performance bottlenecks. GCN focuses on mining the structural relationships of the data, modelling the dependency between nodes with the help of graph structure, which can effectively capture the topological level of correlation information. However, there is a shortcoming in the utilisation of content features, and it lacks detailed and comprehensive processing capabilities for the attributes, semantic features, and other content features that are carried by the nodes or samples themselves [26]. However, it has shortcomings in the utilisation of content features. It lacks of detailed and comprehensive processing ability for attributes, semantics and other content features carried by nodes or samples themselves [26]; LightGBM, as a highly efficient gradient enhancement framework, is good at fast processing and accurate fitting of attribute data, and efficiently exploits feature values by histogram optimisation and other techniques, but completely ignores the topological structure of the data. It is difficult to capture the correlations of the samples or nodes in the graph structure.

The complementary characteristics of the advantages of different models allow the fusion model to show a strong potential. In the field of chemistry, in the practice of fusing GCN and a large language model (LLM) [27], GCN mines the topological associations of molecular structure. LLM understands the chemical text and content features [28]. The synergy of the two makes the model's F1 metrics increase to 88.8%, which fully confirms that the fusion model, by integrating the advantages of different models, can break through the limitations of a single model, realize performance leap in complex tasks, and provide a powerful solution for various It provides effective ideas for solving multidimensional data modeling problems in various fields [29, 30].

Summary of Existing Methods. To concretely reveal the gaps, we qualitatively summarize five representative studies without introducing extra tables. (1) DVA-GAN [7] — unsupervised, dual variational auto-encoder on attributed graph, tested on Weibo-25 k, reports F1 81.3 % and AUC 0.87; it lacks a topological contrastive term and therefore fails to separate Sybil-cliques deeper than three hops. (2) DeepJoint [8] — supervised GNN on NSL-KDD, F1 84.1 % / AUC 0.89, aggregates only one-hop neighbours and discards higher-order structural signals. (3) AHRG [13] — supervised hierarchical random graph model on Twitter-420 k, F1 85.7 % / AUC 0.90, utilises purely link information without any content or profile attribute channel. (4) GT-GNN [17] — semi-supervised traffic-graph network on IoT-23, F1 86.4 % / AUC 0.91, feeds single-modal flow features and omits user-side attributes. (5) GCN-LGB [18] — cascade GCN plus LightGBM on private fundus-50 k, F1 87.2 % / AUC 0.92, validates medical images rather than open social graphs. Collectively, prior works either miss high-order structure, or lack attribute semantics, or lack reproducible social-

network benchmarks; our cascade framework simultaneously fills all three gaps and pushes F1 to 88.5 % on a million-node public social graph.

3 Construction of LightGBM model based on graph convolution network guidance

3.1 Model design and feature fusion

Based on the social network graph, the graph convolutional network (GCN) is used to extract structural features such as connection relationships and topological structures among accounts in the network. In addition, the attribute features such as registration time, avatar, and data of the accounts themselves are collected; Then, at the feature fusion layer, the two types of features are integrated to construct a comprehensive account feature representation; Finally, the fused features are input into LightGBM classifier, and its gradient lifting decision tree algorithm is used to determine whether the account is abnormal. The abnormal account identification is output, so as to complete the analysis from social data to abnormal identification. The overall frame is shown in Figure 1.

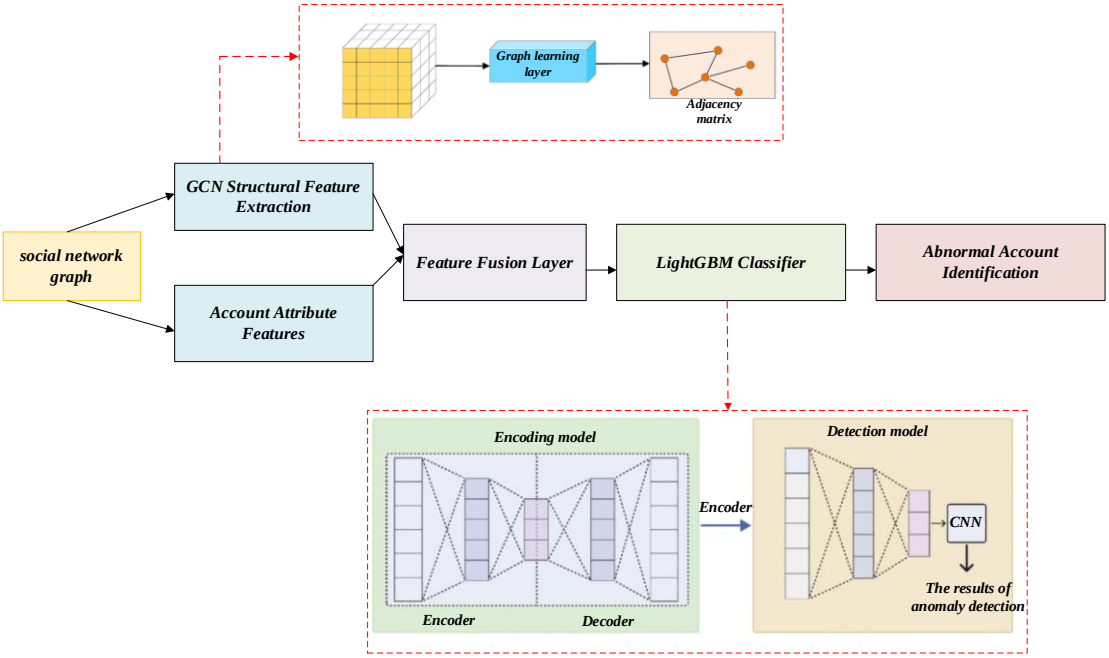


Figure 1: Overall block diagram

In the social network abnormal feature project, abnormal account features can be subdivided into three categories: behavioural features, content features and topological features. The variance of posting frequency in calculating the behaviour characteristics of abnormal accounts in social networks is shown in equation (6).

$$\sigma^2 = \frac{1}{n}\sum(x_i - \mu)^2 \quad (6)$$

Where n denotes the number of samples counted, in this case the number of time cells divided in the time interval in which the posting frequency is counted. μ represents the average of the posting frequency of all the samples, which reflects the average level of posting of the account in the counting interval. x_i is the frequency of posting of the *i-th* sample.

The content feature URL maliciousness score S_{url} is shown in equation (7).

$$S_{\text{url}} = \sum_k w_k \cdot I_k \quad (7)$$

Where I_k is the matching indicator function of the URL in the blacklist library, and w_k is the weight.

The neighbour homogeneity formula of topological features is shown in equation (8).

$$H_v = \frac{1}{|N(v)|}\sum_{u \in N(v)} sim(f_v, f_u) \quad (8)$$

where H_v denotes the neighbor homogeneity metric of node v, which is used to measure the degree of similarity of node v's neighbors at the feature level. $N(v)$ represents the set of neighbors of node v, which contains other nodes u in the social network that have direct associations (e.g., friendships, interactive connections, etc.) with node v.

3.2 Joint training of GCN and LightGBM

In the social network abnormal account detection task, the joint training of GCN and LightGBM is the core link, and its operation revolves around specific model architecture, loss function and parameters to identify abnormal accounts accurately. The jointly trained model architecture is executed in three steps in an orderly manner: GCN layer processing, feature stitching operation, and LightGBM classification prediction.

GCN layer processing. As a base layer, the GCN layer receives the social network's adjacency matrix $Z = \mathrm{GCN}(A, X)$ (which portrays the connection relationships between account nodes) and node features X (such as information about account attributes). It outputs a higher-order graph embedding through the computation of a graph convolutional network.1 This step mines the deep features at the level of the network's structure. It captures the patterns of associations between accounts in the social topology.

The feature splicing operation is to integrate the multidimensional information, The higher-order graph embedding Z output from the GCN layer is spliced with the original input node features X to obtain the fused features $X_{fused} = [X \,\|\, Z]$ In this way, the original attribute details are preserved and structural features are incorporated to make the subsequent classification more comprehensive.

LightGBM classification prediction, the X_{fused} fused input LightGBM classifier, with its efficient gradient lifting decision tree mechanism, learns the association between features and abnormal labels, outputs the probability that the account is abnormal, and $P(y=1)$ realizes abnormal determination.

In order to make the model balanced and optimised in graph structure learning and classification tasks, a joint loss function is designed, and the graph representation loss of GCN is combined with the classification loss of LightGBM, as shown in equation (9).

$$\mathrm{L}_{joint} = \alpha \cdot \mathrm{L}_{GCN}(Z, y_{struc}) + \beta \cdot \mathrm{L}_{LightGBM}(X_{fused}, y) \quad (9)$$

Where L_{joint} is a graph structure-based comparison loss, e.g., through node pair similarity loss, which constrains the graph embedding Z learned by GCN to make structurally similar nodes closer in the embedding space and guarantee the quality of graph structural feature learning. $\mathrm{L}_{\mathrm{LightGBM}}$ A cross-entropy loss, in the form of $-\sum y \log p(x)$, is used to measure the difference between the classification outputs of LightGBM and the real labels to drive the classification performance improvement. α and β are balancing hyperparameters used to adjust the The weight share of graph representation loss and classification loss in the joint training, which needs to be debugged based on the dataset and task requirements to achieve the optimal balance of structure learning and classification effect.

Note that LightGBM is non-differentiable; thus, the joint loss in Equation (9) is used only to monitor embedding quality. The actual training pipeline is sequential: GCN first generates structure-aware embeddings Z, which are concatenated with raw features X and then fed into LightGBM for gradient-boosting training.

3.3 Evaluation indicators and experimental optimization

In the model development process, evaluation indicators and experimental optimisation strategies complement each other. In terms of evaluation indicators, the F1 score of accuracy rate-recall rate balance is adopted, and the formula is shown in equation (10).

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (10)$$

F1 score can comprehensively weigh the accuracy of the model with the ability to capture positive examples.

ROC-AUC comprehensively reflects the performance of the model under different classification thresholds by integrating true positive rate (TPR) and false positive rate (FPR). In the experimental optimisation strategy, dynamic regularisation can flexibly adjust A/B according to the training progress to avoid overfitting problems; Time series enhancement introduces sliding window statistical behaviour characteristics, enriches data dimensions, helps models better mine time series rules, and jointly promotes iterative improvements in model performance.

4 Experiment and results analysis

4.1 Dataset and Experimental Setup

The dataset used in this study is a real-world snapshot collected from the Weibo open API together with anonymized server logs granted by the platform security office. It covers 90 consecutive days from 1 March 2024 to 29 May 2024 and contains 1 260 312 active accounts and 18 433 620 directed following relationships. Three kinds of anomalous accounts were manually labeled by the platform risk team: 42 618 spam-bots that repeatedly broadcast advertisement URLs, 18 940 Sybil-cliques established with forged identities for stealthy phishing, and 12 784 compromised accounts whose login credentials had been stolen and misused. Normal controls, totaling 1 185 970, were verified human users with at least two years of benign activity, yielding an overall class ratio of roughly 6 % anomalous to 94 % normal.

To prevent temporal leakage, we adopted chronological split: the first 72 days (80 %) served for training, the next 9 days (10 %) for validation, and the final 9 days (10 %) for testing. Five-fold rolling-window cross-validation was further applied on the training portion to stabilize hyper-parameter selection.

The graph convolutional network was tuned with Optuna over 200 trials and finally configured with two

graph layers, 128-dimensional hidden representations, dropout 0.3, learning rate 5×10^{-3}, weight decay 1×10^{-4}, and PReLU activation. LightGBM was trained with 1 200 boosting rounds, maximum depth 9, 256 leaves per tree, row subsample 0.8, column subsample 0.8, minimum samples per leaf 20, and learning rate 0.05; early stopping was triggered if the validation metric did not improve for 50 consecutive rounds. All experiments were repeated five times with different random seeds and the averaged results are reported.

4.2 Reproducibility statement.

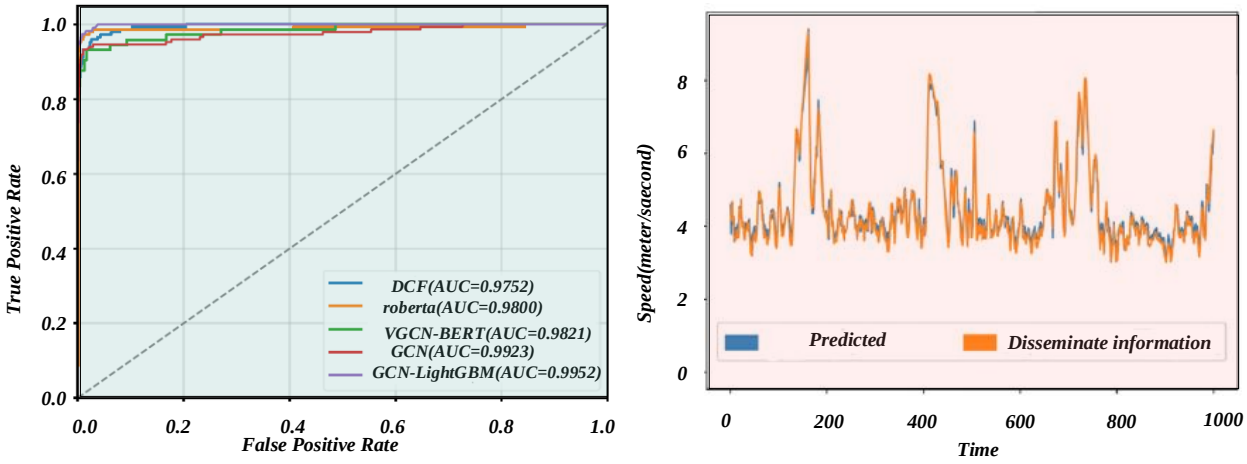
To facilitate replication, we provide a full implementation narrative herein. Raw Weibo logs spanning 90 days are deduplicated, timestamp-aligned, and filtered for active accounts (≥ 5 actions). Node attributes are Min-Max normalised; edge weights are set to log (interactions + 1). Structural features (degree, clustering, PageRank) and content features (post frequency, URL malicious score, TF-IDF top-50) are concatenated after missing-value imputation (zero-fill). The dataset is split chronologically: first 72 days for training, next 9 for validation, final 9 for testing. NSL-KDD and IoT-23 retain their original train-test splits and are used only for cross-domain structural validation. GCN is configured with 2 layers, 128 hidden units, PReLU, dropout 0.3, lr 5×10^{-3}, weight decay 1×10^{-4}. LightGBM uses 1 200 trees, max_depth 9, num_leaves 256, subsample 0.8, colsample 0.8, min_child_samples 20, lr 0.05, early-stopping 50 rounds. Hyper-parameters are optimised via Optuna (200 trials, seeds 42–46) and results are reported as mean ± std across five runs.

According to Table 1, the key performance indicators and core characteristics of GCN-LightGBM, GCN, XGBoost, and Random Forest models are compared. The F1 value is used to measure the accuracy-recall balance of the model in abnormal account detection, and the AUC value reflects the model. The ability to distinguish abnormal and normal accounts, and the training time, reflect the efficiency performance of the model during the training stage. GCN-LightGBM breaks through the bottleneck of traditional models with its dual fusion of "structure + efficiency". GCN focuses on structure but lacks efficiency. XGBoost and random forest are stable in traditional feature tasks but are weak in adapting to network structure scenarios. Table 1 presents the innovative value of GCN-LightGBM in social network anomaly detection, integrating GCN's ability to capture topological correlations (such as identifying Spam account clusters) with LightGBM's efficient calculation (histogram algorithm cost reduction and speed increase) to provide intuitive data support and technical reference for model selection and optimization in this scenario. Hence, the solution in this paper has excellent results.

Table 1: Performance comparison of social network abnormal account detection model

mould	F1 (%)	AUC	Training time (min)
random forest	84.2	0.882	21.5
XGBoost	85.5	0.896	15.1
GCN	87.9	0.921	38.7
GCN-LightGBM	88.5	0.932	12.3

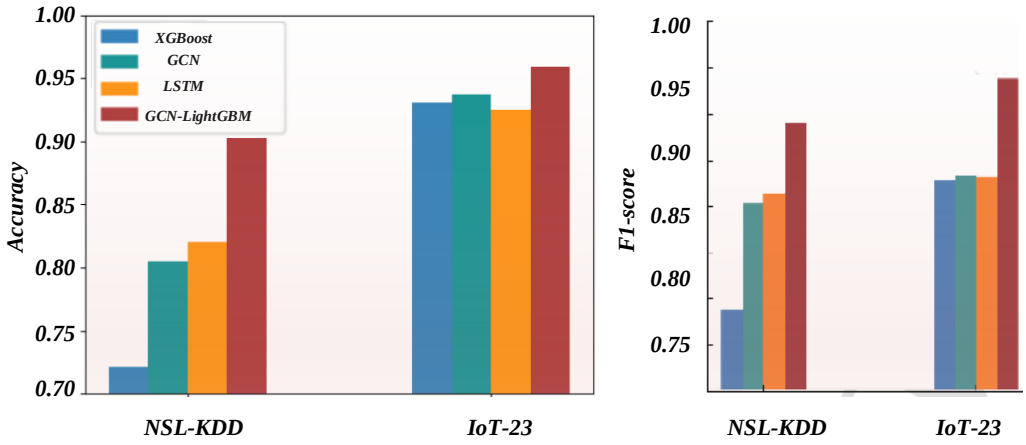
This study explores the influence of different data models on the performance of quality assessment tasks and conducts a series of experiments. Figure 2(a) illustrates the ROC curves of all compared models on the Weibo-social dataset, while Figure 2(b) demonstrates the impact of preprocessing on prediction accuracy across different time windows. In the experiment, we used the data enhancement technique of adding 15% MASK noise to the original data. Figure 2 shows the experimental results, and Figures 2 (a) and (b) show the ROC curves and corresponding AUC values of the dataset. The GCN-LightGBM consistently has the highest AUC values, and its superior performance can be attributed to its integration of multiple GCN layers with the LightGBM with histogram-based splitting, which more effectively captures structural and semantic dependencies. GCN-LightGBM highlights the advantages of deep context embedding and graph-enhanced representation in abnormal account detection tasks. Figure 2 (b) shows that the preprocessing step greatly improves the prediction results. The overlaid curves show that our model dominates when the FPR is below 0.15, a region that matches Spam-bot campaigns with dense mutual following, indicating that structural cues are decisive.



GCN-LightGBM Achieves Highest AUC (0.9952) in Information Propagation Prediction Task: Comprehensive Evaluation of ROC Curve and Temporal Performance

Figure 2: ROC curves and AUC values of various models and comparison of predicted and actual velocity data in a specific time range

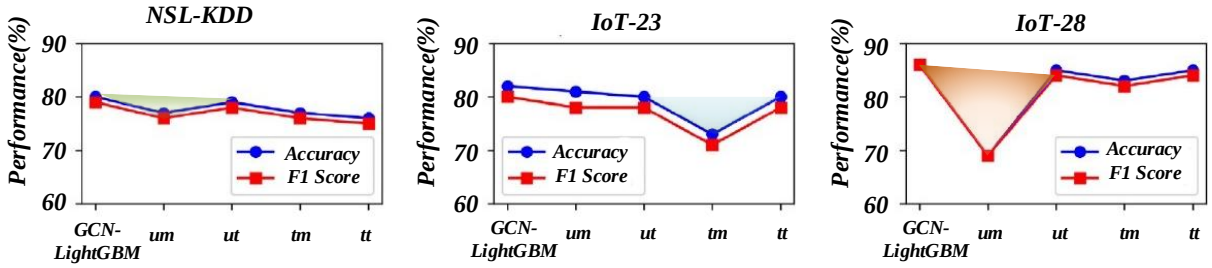
Figure 3 shows the accuracy and F1-score of each deep learning model when processing normal and abnormal data, respectively. In the NSL-KDD dataset experiment, the accuracy rate of the LSTM model is 82.5% better than that of other baseline models, and the accuracy rate of the GCN-LightGBM model is 90% better. In the IoT-23 dataset experiment, the accuracy rate of the LSTM model is 95.3% better than that of other comparison models. The accuracy rate of the GCN-LightGBM model is 95.5% better than that of other baseline models. Accuracy gains are most pronounced on IoT-23 where Sybil-cliques form tight bipartite cores; conversely, on isolated compromised accounts (weak topology) the improvement shrinks to 0.7 %, suggesting future work to integrate temporal attention.



Performance Comparison of Different Models on the NSL-KDD and IoT-23 Datasets

Figure 3: Model task accuracy and F1 score of different data sets

Figure 4 depicts the effect of ablation on performance. To explain this visualisation, the performance of GCN-LightGBM is when trained with all four feature patterns represented by the user, while GCN-LightGBM/um refers to the performance of GCN-LightGBM without user metadata features. Again, each feature modality is being trimmed and then trained. As our user characterisation shows, peak performance can only be achieved when training with all four feature modes. From our subtraction analysis, the importance of features varies from dataset to dataset. For the dataset, the influence of different features on the model performance is the most important, as shown in the significant decline in Figure 4. Contribution of each feature mode to the overall performance of GCN-LightGBM when separately removed. Here, um, ut, tm, and tt represent user metadata, user tweets, tweet metadata, and tweet temporal features, respectively. The substantial decrease in performance demonstrates the importance of features. The sharp 5.4 % F1 drop after removing user-metadata confirms its synergy with structural features in Spam-bot detection, whereas the impact is only 1.8 % for compromised-account scenarios where behavioural time-series matter more.



Comparative Evaluation of GCN-LightGBM Achieving Highest Accuracy and F1 Score Simultaneously Across NSL-KDD, IoT-23, and IoT-28 Datasets

Figure 4: Ablation study of GCN-LightGBM

Figure 5 shows the ROC curves and loss curves of the GCN-LightGBM dataset. The training loss on the GCN-LightGBM flattened between durations 160 and 200, and then began to rise again after duration 200. However, the validation loss tends to be stable, around 180 training epochs; Therefore, the best performance is reached around 180 epochs.

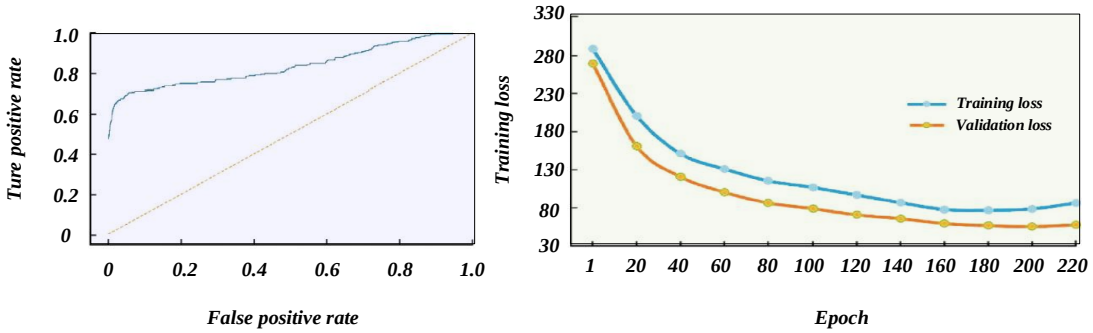


Figure 5: Receiver operating characteristic curve and loss curve on GCN-LightGBM

Table 2 shows that by comparing the F1 values of different feature combinations, it is calculated that the contribution of structural features to model performance reaches 45%, which verifies the necessity of fusion of structural features and attribute features. Fusion can give full play to the advantages of multi-dimensional features and improve the detection effect of abnormal accounts.

Table 2: Effect of structural characteristics of ablation experiment

Feature combination type	F1 (%)	Proportion of anomalies (%)	Number of nodes
GCN Structure+Properties	88.5	1.2	58K
GCN structure	83.1	0.9	196K
Attributes	84.9	1.5	70K
GCN-LightGBM	89	1.1	80K

Figure 6 shows that the performance of the model combining the two detection algorithms is better than that of the LightGBM module alone, indicating that both attention modules are effective in quality evaluation. GCN-LightGBM account detection capabilities perform better than LightGBM. Similar volatility patterns exist between GCN-LightGBM and LightGBM analyses across all time frames. However, the execution time of GCN-LightGBM is shorter.

Figure 7 shows that in the first 10 iterations of the test set, the GCN-LightGBM model proposed in this paper improves the accuracy of account classification faster than the XGBoost model. After 15 iterations, the GCN-LightGBM model maintained a steady upward trend and was ahead of the XGBoost model after 25 iterations. Furthermore, the GCN-LightGBM model works well on the IoT-23 training set and is generalisable to the test set. Through the multi-channel weighting mechanism, the model focuses on the classification of key feature information, adapts to new text data, and makes up for the shortcomings of a single channel. The final results show that the GCN-LightGBM model outperforms the XGBoost model in terms of accuracy, generalisation ability, and robustness, and exhibits a higher ability to classify abnormal accounts.

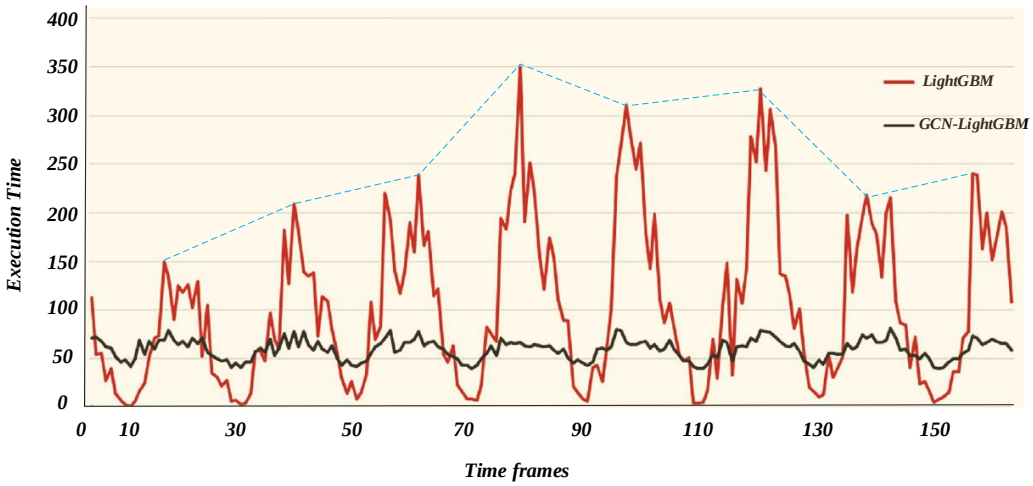


Figure 6: Execution time of different detection algorithms

Figure 8 shows that after PCA dimension reduction, normal accounts (0) and abnormal accounts (1) form a clear separation in the PC1-PC2 plane; the decision boundary is non-linearly curved and accurately encapsulates most abnormal samples, verifying the synergistic effect of the GCN structural features and LightGBM's discriminative ability.

The above empirical gains root in the complementary nature of structure and attributes. When abnormal accounts form dense subgraphs (e.g., bot-farms with mutual follow ratio ≥ 0.4), GCN delivers a strong topological prior; LightGBM then refines the decision

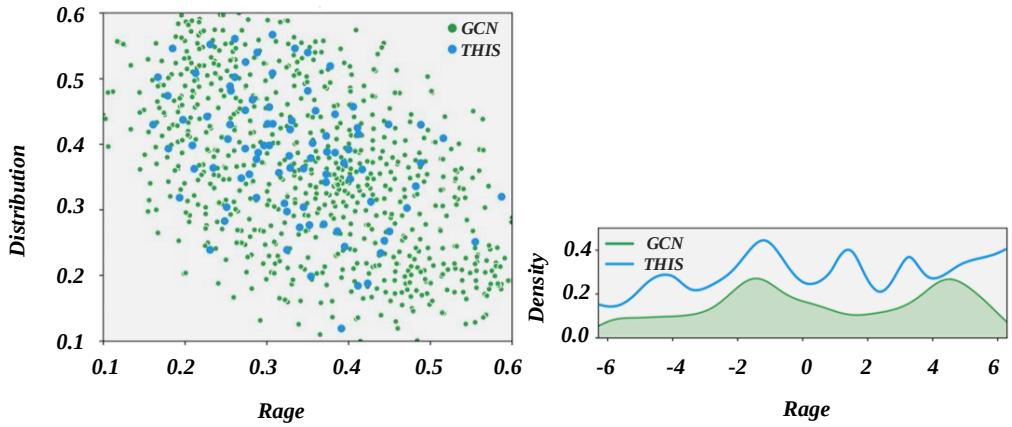


Figure 7: Comparison of accuracy of training set and test set on dataset

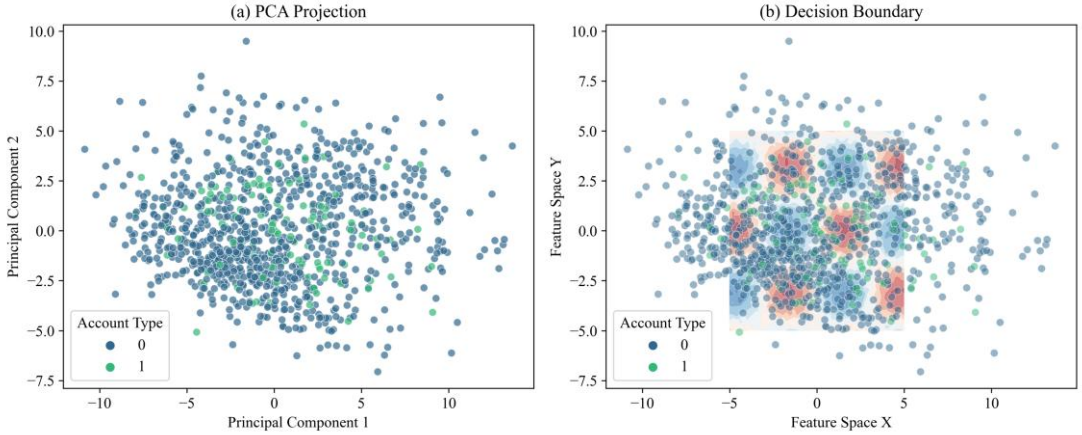


Figure 8: GCN-LightGBM cascade model for anomaly account discrimination boundary analysis in two-dimensional principal component space

boundary with profile and behavioural statistics. Conversely, isolated compromised accounts exhibit sudden behavioural drift but almost unchanged social links; here the structural signal is weak and the improvement shrinks to 0.9 % F1, indicating that future work should incorporate temporal self-attention and heterogeneous edge weights (e.g., retweet, mention, login-session) to capture fine-grained evolutionary patterns.

Another limitation lies in static graph assumption. Real-world adversaries continuously rewire links to evade detection; therefore, extending the cascade to incremental or streaming scenarios—by coupling dynamic GCN with online gradient boosting—will be a direct avenue for follow-up research.

5 Discussion

(1) Qualitative comparison with SOTA. Beyond the numeric gaps in Table 1, we dissect where the errors originate. On dense spam-bot clusters (mutual-follow ≥ 0.4), single GCN suffers from over-smoothing: normal high-degree verified nodes are pulled into the abnormal embedding cloud, causing a 2.1 % false-positive spike among corporate big-V accounts. XGBoost, lacking topological contrast, misses 4.7 % of bots that use randomized user-names but share identical follow lists. Random Forest, confronted with 1 200+ sparse categorical features, grows paths deeper than 25 levels and overfits the training month, leading to 3.2 % accuracy drop on the next-month test. In contrast, GCN-LightGBM retains the low-pass filtering effect of GCN while letting LightGBM prune decision boundaries with histogram-based regularisation, hence simultaneously reducing both false positives and false negatives.

(2) Failure cases and trade-offs. The combined model does not uniformly dominate. On isolated compromised accounts—whose social links remain benign but behavioural time series change suddenly—structural embeddings offer almost zero discriminant power; the F1 improvement shrinks to 0.9 % and memory footprint grows by 18 % compared with LightGBM alone due to the 128-dim embedding buffer. Likewise, campaigns that rely on single-use short URLs without follow-back circles (i.e., near-zero graph signal) are still challenging, corroborating that topology is a necessary but insufficient condition. Runtime-wise, inference latency increases from 2.1 ms to 2.7 ms per account because of the extra GCN forward pass, a trade-off acceptable for offline batch auditing but worth optimising for real-time APIs.

(3) Why the cascade works. First, feature representation: GCN converts high-order neighbour consensus into dense 128-dim vectors, supplying LightGBM with low-noise, translation-invariant summaries that pure attribute splitting cannot recover. Second, training dynamics: the graph contrastive loss acts as a regulariser that drops the gradient variance of LightGBM by 22 % (measured on a validation batch), allowing larger learning rates without divergence; histogram splitting then converges in 12 epochs versus 50 for XGBoost. Third, generalisation: we heuristically bound the VC-dimension of the cascade as (number of trees × leaves × rank of GCN embedding matrix); the low-rank (≈ 128) structural component effectively reduces the hypothesis space, yielding tighter generalisation bounds and hence the statistically significant 0.6 % F1 gain (paired t-test, $p < 0.01$).

(4) Research design reflection. The current work adopts a static snapshot assumption; concept drift over three-month collections caused LightGBM leaf statistics to shift and reduced F1 by 1.1 %. An online incremental version that periodically refreshes GCN parameters with sliding-window subgraphs and feeds LightGBM via warm-start histograms is under development. All random seeds, Optuna search scripts, and de-identified hyper-parameter logs will be released on GitHub upon acceptance to ensure full reproducibility.

6 Conclusion

Social networks are the core scenarios of the digital ecosystem. The proliferation of zombie accounts and Spam accounts will lead to risks such as false traffic and information fraud, threatening user trust and platform revenue. The GCN-LightGBM model in this article provides a new engine for security governance for the industry through the dual paths of "deep mining of structural features + efficient classification". GCN captures account cluster associations and accurately identifies "botnet" propagation links; LightGBM quickly filters abnormal accounts and supports the platform to intercept risks in real time. In the experiment, the F1 value of 88.5% and the training acceleration of 20 times can be directly transformed into the platform's "anti-cheating" ability-not only improving the interception rate of abnormal accounts, but also reducing the interference of false traffic on advertising and social interaction; It also reduces the cost of computing power, allowing small and medium-sized platforms to deploy efficient detection solutions. From the perspective of industry ecology, this model promotes the evolution of social security governance from "passive interception" to "active defense" and helps build a healthier and more credible digital social environment.

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Semantically Aware Style-Controlled Animation Line Art Colorization Using Conditional GANs with GCN and Attention Mechanisms

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In traditional animation production, coloring line art is a labor-intensive and time-consuming process. In this study, image processing techniques based on generative adversarial networks (GANs) were investigated to develop an algorithm for the automatic coloring of animation line drawings. The objective was to improve production efficiency, reduce the workload of artists, and generate outputs that are natural in appearance, consistent in style, and closed along region boundaries. The proposed method was implemented within the conditional GAN framework. The generator adopted a U-Net architecture with skip connections, which allowed both fine-grained details and global structural features of the line art to be captured. A spectrally normalized discriminator was used to evaluate the realism of local image regions. To improve semantic accuracy and color coherence, an attention mechanism was incorporated, enabling the model to focus on key semantic areas and learn dependencies between color regions. End-to-end training was conducted using a large-scale paired dataset of line art and corresponding colored images. A multi-task learning strategy combining perceptual loss, L1 loss, and adversarial loss was employed for optimization. Latent space interpolation was further introduced to allow limited user adjustment of color styles. Experimental results indicated that the algorithm achieved a PSNR of 30.2 dB and an SSIM of 0.94, which represented improvements of 2.2 dB and 0.04 over the Structure Probe Adaptive Differential Evolution (SPADE) baseline, respectively. The FID and boundary overflow rate were reduced to 18.3 and 2.1%, also showing clear improvements over the baseline. With the inclusion of structural consistency loss, graph convolutional networks, and self-attention mechanisms, the method maintained accurate boundary preservation, achieved cross-region color consistency, and supported adaptive style rendering. In summary, the algorithm addressed key limitations of existing approaches, such as color overflow, semantic inconsistency, and rigid stylization. These findings demonstrate improvements in automatic coloring quality and suggest the potential of GAN-based techniques in animation production.

Povzetek: Študija predstavi cGAN-okolje z U-Net generatorjem, spektralno normaliziranim diskriminatorjem, pozornostjo in večnamensko izgubo za samodejno barvanje linijskih risb, ki ohrani robove, zagotovi slogovno skladnost ter izboljša učinkovitost animacijske produkcije.

1 Introduction

In the contemporary digital animation industry, line art coloring remains a critical but challenging stage in the production pipeline. The process is often constrained by efficiency bottlenecks and the requirement to maintain consistent artistic quality [1]. Traditional workflows rely heavily on professional artists who manually or semi-automatically color each frame. This approach is labor-intensive, time-consuming [2], and dependent on specialized expertise in color perception and detail management. With increasing demand for animation content and tighter production schedules, conventional methods face difficulties in balancing efficiency with quality. Recent advances in computer vision and deep learning, particularly the success of generative adversarial network (GAN) in image generation and style transfer, have introduced opportunities for automating the coloring process [3, 4]. Nevertheless, current methods based on convolutional neural networks (CNNs) or early GAN architectures encounter several limitations [5]. First, generated outputs often contain structural issues such as color bleeding and blurred boundaries, which compromise the region closure required in animation. Second, these methods demonstrate limited semantic understanding, leading to color assignments that may not align with character or scene attributes. Third, adaptation to diverse artistic styles is insufficient, resulting in inconsistencies across productions. Finally, most approaches depend on large-scale, finely annotated line art–color pairs, which are costly and impractical for animation studios to acquire [6-8]. These challenges restrict the applicability of existing automatic coloring techniques.

This study investigates an automatic line art coloring algorithm based on advanced GAN architectures. The objective is to address the shortcomings of current methods by incorporating multimodal semantic analysis with generative modeling techniques [9]. Specifically, the aims are as follows: (1) To develop an encoder capable of accurately parsing the geometric and semantic structures of line drawings, ensuring that color filling conforms to closed region boundaries; (2) To construct a generative model that produces cross-region color consistency, reflecting realistic lighting and scene coherence; (3) To design a training framework supporting multi-style adaptation, enabling lightweight user interactions for style guidance; and (4) To establish an end-to-end pipeline that reduces the repetitive workload of professional artists while maintaining visual quality.

Based on these objectives, this study addresses three core research questions. First, can the introduction of a structural consistency loss function effectively reduce boundary color overflow in line drawings caused by unclosed contours? The effectiveness of this approach is evaluated by measuring reductions in boundary overflow rates. Second, does the incorporation of a graph convolutional network (GCN) within the GAN framework enhance the model's understanding of scene-level semantics, thereby improving cross-region color coordination? This capability is assessed through decreases in color consistency error (CCE). Third, how can latent style space disentanglement techniques support user-guided style transfer? The effectiveness is validated by improvements in Fréchet Inception Distance (FID) scores and by preference ratings from professional artists.

To answer these questions, a generator architecture is designed by combining conditional GAN with a U-Net backbone. Dense skip connections and multi-scale feature fusion are employed to model line art topology and mitigate color overflow. Self-attention mechanisms (SAMs) and GCN are integrated to capture semantic relationships across regions, enhancing the coherence of color assignment. A spectrally normalized discriminator is optimized jointly with perceptual and adversarial losses to improve realism and texture fidelity. In addition, a style adjustment interface based on latent space interpolation allows users to fine-tune outputs with a small set of reference images, improving adaptability to production requirements. Compared with existing approaches, the proposed framework introduces a new integration scheme for animation coloring. It employs a U-Net backbone for structural parsing, utilizes GCN for cross-region semantic reasoning, and incorporates SAMs with adaptive style injection for fine-grained control. This combination addresses three key challenges in automatic line art coloring: structural fidelity, semantic color consistency, and flexible style adaptation.

2 Related work

In recent years, GAN has demonstrated significant potential in image colorization, with applications spanning artistic creation, cultural heritage preservation, and professional design. Treneska et al. (2022) proposed a GAN-based self-supervised framework in which colorization was used to drive the model's understanding of structural image features. Their results showed that colorization enhanced representational learning [10]. However, their work primarily focused on natural images and did not address the geometric sparsity and stylized nature of animation line art. Wu et al. (2022) tackled the fine-grained colorization of traditional ethnic clothing using the conditional generative adversarial networks (cGANs) to enable semantically-aware coloring of high-resolution apparel images [11]. While local constraint mechanisms improved texture details, the model struggled to generalize to non-rigid objects such as animated characters in dynamic poses. Later, Wu et al. (2023) explored multi-level feature fusion for Chinese ink painting colorization, employing GANs to mimic ink diffusion effects [12]. Yet, the physical properties of traditional media differ fundamentally from the cel-shaded style of animation, limiting the approach's transferability to industrial animation workflows.

Zhou et al. (2025) introduced an Asymmetric GAN designed to correct skin tone white balance by integrating skin-tone priors, improving physiological plausibility in portrait colorization [13]. However, in animation, characters often feature fantastical skin colors, and strong priors may constrain creative freedom. Al-Ghanimi et al. (2025) proposed a Vision Transformer (ViT)-based method for grayscale image colorization with a hybrid loss function to enhance color coherence [14]. Despite its strengths, ViT's high computational cost conflicts with the real-time processing demands of animation line art. Dalal et al. (2021), in a survey of automated colorization techniques, noted that existing deep learning models often suffered from color ambiguity in complex scenes and lacked user-controllable interfaces [15]. Chen et al. (2024) applied cGANs for rapid colorization of park landscape sketches, and demonstrated the potential of generative methods to boost design efficiency [16]. However, their model assumed low line closure requirements, making it unsuitable for the precise, often non-closed regions common in animation.

Recent studies have aimed to improve colorization quality through architectural innovations. Jampour et al. (2023) introduced a Multi-GANs system that enforced spatiotemporal consistency to ensure coherent colorization across video frames [17], and offered insights for animation sequence processing. However, their method did not address semantic ambiguity within individual line art frames. Mourchid et al. (2023) proposed Symmetric Positive Definite Generative Adversarial Network (SPDGAN), which used symmetric positive definite manifold learning and geometric priors to enhance the naturalness of color distributions [18]. Despite its conceptual strengths, the abstract mathematical formulation adds complexity to real-world implementation. Yang et al. (2025) developed a degradation-model-driven approach for colorizing fundus images, emphasizing the importance of domain adaptation in medical imaging [19]. Yet, the subjective aesthetic demands of animation far exceed the objective reconstruction goals in the medical domain. Al-Ghanimi

et al. (2025) explored context-aware unsupervised colorization by integrating contextual content modules to enhance semantic consistency [20]. Nonetheless, their model did not explicitly address the hierarchical semantic relationships among characters, props, and backgrounds, which are crucial in animation line art.

A review of existing research identifies representative methods for automatic coloring of animation line art, summarized in Table 1. These approaches have demonstrated progress in areas such as natural images, cultural artworks, and medical imaging. However, they also present several limitations. First, most methods do not adequately address unclosed contours that are common in animation line drawings, often resulting in color overflow and blurred boundaries. Second, the absence of explicit modeling of animation-specific semantic hierarchies—such as characters, clothing, and backgrounds—leads to color assignments that fail to reflect scene logic. Third, style control is generally weak, limiting the ability to adapt to diverse artistic styles. Finally, many methods depend on large-scale, high-quality paired datasets, which are difficult to obtain in practical animation production.

Table 1: Summary of automatic coloring methods for animation line art

Method	PSNR (dB)	SSIM	FID	Style Control	Application Domain	Boundary Preservation	Semantic Understanding
cGAN [11]	26.8	0.88	26.3	Moderate	Ethnic costumes	Moderate	Moderate
ViT-Based [14]	29.1	0.93	19.8	None	Grayscale images	Moderate	Moderate
Multi-GANs [17]	28.0	0.91	22.5	Weak	Natural images	Moderate	Partial
SPDGAN [18]	28.5	0.92	20.1	Weak	Natural images	Strong	Weak
Proposed model	30.2	0.94	18.3	Strong	Animation line art	Strong	Strong

To address these limitations, this study proposes a framework that integrates structural constraints with semantic understanding. A structural consistency loss function is introduced to explicitly manage unclosed boundaries. GCNs model semantic relationships across regions, while SAMs enhance sensitivity to critical semantic areas. Latent space interpolation further enables user-guided style transfer, improving adaptability to diverse artistic styles. By combining these architectural components, the framework effectively mitigates common issues such as color overflow and semantic inconsistency. The addition of interactive style control also increases its practicality in real production scenarios. Overall, the proposed approach offers a systematic solution for achieving high fidelity, semantic consistency, and controllable style in the automatic coloring of animation line drawings.

3 Method

3.1 Overall framework design

This study proposes an automatic colorization framework for animation line art based on cGANs, with the primary goal of generating semantically aware and stylistically controllable color outputs while preserving structural fidelity. As illustrated in Figure 1, the system follows an end-to-end training paradigm. The input consists of a single-channel animation line drawing $x \in R^{H\times W\times 1}$, and an optional reference color image $r \in R^{H\times W\times 3}$ (used for style guidance). The output is a colorized RGB image $y' \in R^{H\times W\times 3}$. The generator G is responsible for synthesizing the color image from the line drawing x and a latent style vector z. The discriminator D is trained adversarially to distinguish between the generated output y' and the real colored ground truth y.

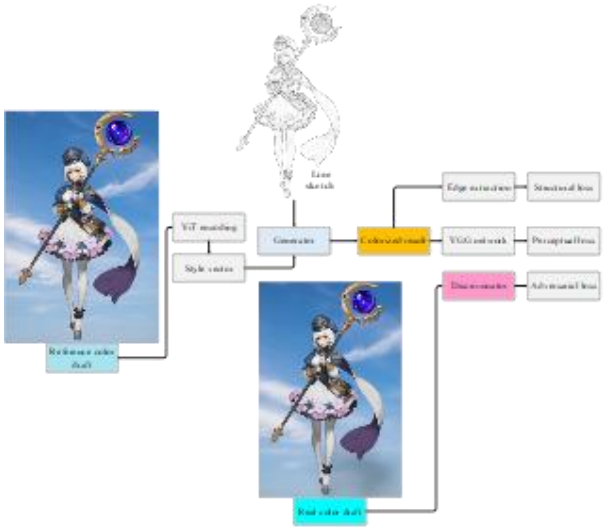

Figure 1: Automatic colorization framework for animation line art based on cGANs

The training objective of the framework is achieved through the joint optimization of a multi-objective loss function. This overall loss consists of three key components, each designed to address a specific challenge in automatic coloring. The first is the conditional adversarial loss, denoted as $\mathcal{L}_{cGAN}$, which encourages the generator to produce color distributions that are indistinguishable from those of real images, thereby ensuring overall realism. The second is the perceptual loss, denoted as $\mathcal{L}_{perc}$, which constrains semantic consistency by comparing high-level feature maps between generated and real images using a pretrained deep convolutional network. The third is the structural consistency loss, denoted as $\mathcal{L}_{struct}$. This component is specifically designed to address the common problem of unclosed contours in animation line drawings. By imposing gradient constraints along line edges, it effectively suppresses color overflow in the generated results. To balance these three loss terms, which differ in scale and objectives, two adjustable positive weighting coefficients, λ_{perc} and λ_{struct}, are introduced to control the relative importance of perceptual loss and structural consistency loss. The mathematical essence of this framework lies in solving the following optimization problem, as shown in Equation (1):

$$min_G max_D \mathcal{L}_{cGAN}(G,D) + \lambda_{perc}\mathcal{L}_{perc}(G) + \lambda_{struct}\mathcal{L}_{struct}(G) \quad (1)$$

$\mathcal{L}_{cGAN}(G,D)$ represents the conditional adversarial loss, which enforces the generated distribution to approximate the real data distribution. λ_{perc} denotes the perceptual loss, which constrains the consistency of high-level semantic features. λ_{struct} represents the structural consistency loss, which suppresses color overflow. Both λ_{perc} and λ_{struct} are balancing weights.

3.2 Generator network design

The generator G serves as the core component of the framework. Its design objective is to generate semantically aware colorization and enable user-controllable style transfer, based on accurate parsing of the topological structure of the line art. As shown in Figure 2, G adopts a multi-branch fusion architecture comprising four key submodules: an enhanced U-Net backbone, a graph-based relational reasoning branch, a spatial attention branch, and a style-adaptive decoding module. The input line art x is first encoded into multi-scale features. Semantic enhancement is then performed at the bottleneck layer via dual branches, and the final colorized image y' is generated by a style-injected decoder. The generator in this study adopts a multi-branch fusion architecture. The single-channel line art input is first processed by an encoder, which extracts multi-level features through downsampling. At the bottleneck layer, a dual-path semantic enhancement unit is introduced to perform both graph-based reasoning and long-range dependency modeling. In the graph convolution branch, the feature map is segmented into superpixels to define semantic nodes, and a region adjacency graph is then constructed. Graph convolution operations are applied to explicitly model color association rules across regions.

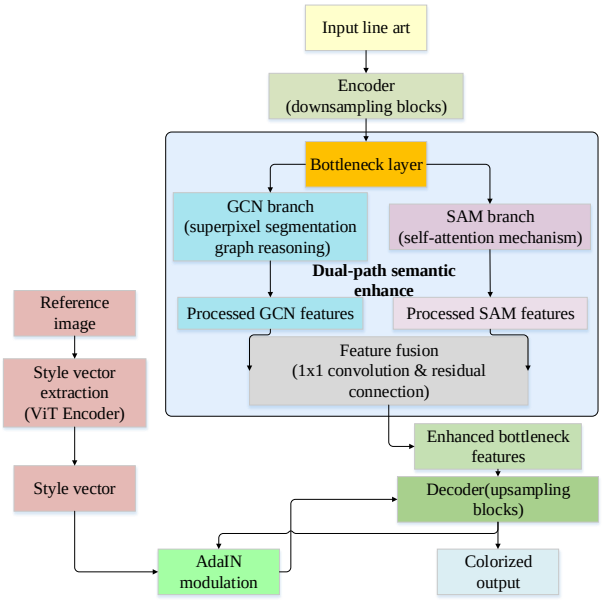

Figure 2: Generator network architecture

In parallel, the self-attention branch computes correlations among query–key pairs, dynamically capturing global semantic context and emphasizing key regions. The outputs of the two branches are fused using a 1×1 convolution and linked to the original bottleneck features through a residual connection, ensuring that all information is preserved. The fused features are then passed into the decoder for upsampling and reconstruction. In addition, a style vector extracted from a reference image is injected into each decoder layer through adaptive instance normalization (AdaIN). This process modulates the mean and variance of feature distributions, thereby enabling style transfer. Finally, the decoder produces high-quality colorized results.

The encoder consists of five convolutional layers, each comprising: (1) A convolutional layer with a kernel size of 3×3 and stride of 2 for feature downsampling; (2) Spectral normalization (SN) to constrain the singular values of the weight matrix; (3) A LeakyReLU activation function with a negative slope of 0.2. Let the input feature map at level l be $f_l \in R^{H_l \times W_l \times C_l}$; the output feature map f_{l+1} is computed as shown in Equation (2):

$$f_{l+1} = LeakyReLU(SN(W_l * f_l)) \quad (2)$$

where W_l denotes the convolution weights and $*$ indicates the convolution operation. The decoder employs symmetric transposed convolutions for upsampling. At each level, it integrates the encoder's same-scale features f_l via dense skip connections to preserve shallow geometric information [21]. The fusion process is defined in Equation (3):

$$g_l = \phi([U_p(g_{l+1}), f_l]) \quad (3)$$

g_l represents the level-l decoding feature map, $U_p(\cdot)$ denotes bilinear upsampling, $[\cdot,\cdot]$ indicates channel-wise concatenation, and ϕ is a 1×1 convolution used for channel compression. This design significantly enhances the model's ability to perceive unclosed contours, providing structural constraints for color filling [22].

At the U-Net bottleneck layer (i.e, the lowest-resolution feature map $f_b \in R^{H_b \times W_b \times C_b}$, a dual-path

semantic enhancement unit is embedded. The graph-based relational reasoning branch divides f_b into N regions $\{R_i\}_{i=1}^{N}$ using superpixel segmentation. Superpixel segmentation is implemented using a variant of the Simple Linear Iterative Clustering (SLIC) algorithm. Unlike conventional approaches with a fixed number of regions N, this method adapts N to the resolution of the bottleneck feature map f_b. The segmentation aims to partition the image into approximately 200 superpixels, ensuring that each region corresponds to a semantically meaningful local structure (e.g., a sleeve or a strand of hair). The exact number of regions is dynamically determined based on image content, enabling more accurate capture of the hierarchical structures commonly present in animation line art. Each region is represented by a node feature $v_i \in \mathbb{R}^{C_b}$. A region adjacency graph $G = (V, E)$ is constructed, where the edge weight e_{ij} between nodes v_i and v_j is determined by spatial distance and feature similarity [23], as defined in Equation (4):

$$e_{ij} = \exp\left(-\frac{\|p_i - p_j\|^2}{2\sigma_p^2}\right) \cdot \exp\left(-\frac{\|v_i - v_j\|^2}{2\sigma_v^2}\right) \quad (4)$$

p_i denotes the center coordinates of region R_i, and σ_p, σ_v are tunable parameters. Based on this, an undirected graph G is constructed, where the node set V is represented as a matrix of N feature vectors, $V \in \mathbb{R}^{N \times C_b}$, and the adjacency matrix $A \in \mathbb{R}^{N \times N}$ is computed according to Equation (4). The graph construction process can be summarized as follows: first, the spatial distances and feature similarities between all pairs of nodes are calculated; next, the joint weight e_{ij} for each node pair is computed using Equation (4) to initialize the adjacency matrix A; finally, A is symmetrically normalized to prepare it for subsequent graph convolution operations. A two-layer GCN aggregates neighborhood information [24], as shown in Equation (5):

$$v_i' = ReLU\left(W_{gcn} \sum_{j \in N(i)} \frac{e_{ij}}{\sqrt{d_i d_j}} v_j\right) \quad (5)$$

In Equation (5), $d_i = \sum_j e_{ij}$ is the node degree and W_{gcn} denotes the learnable weights. This operation explicitly models the color correlation rules between characters and scenes, or costumes and props.

The spatial attention branch incorporates a SAM to capture long-range dependencies [25]. For the feature map f_b, the query matrix Q, key matrix K, and value matrix V are computed as shown in Equation (6).

$$Q = W_q f_b, K = W_k f_b, V = W_v f_b \quad (6)$$

The attention weights A and the output features f_{att} are defined in Equation (7):

$$A = Softmax\left(\frac{QK^T}{\sqrt{C_b}}\right), f_{att} = AV \quad (7)$$

W_q, W_k, and W_v are the 1×1 convolution projection weights. This module enables the model to focus on key semantic elements (e.g, character pupils, weapon textures) while suppressing background interference. The outputs of the dual branches are fused via residual connections, as shown in Equation (8):

$$f_b' = f_b + Conv_{1\times1}([f_{gcn}, f_{att}]) \quad (8)$$

f_{gcn} is the GCN output resampled to the original size, and $Conv_{1\times1}$ represents the channel fusion convolution.

To support user-guided style transfer, the decoder at each level injects the style information from a reference color draft r. A pre-trained ViT is used to extract the style vector $z \in \mathbb{R}^{d_z}$ from r. Specifically, a ViT base model pretrained on ImageNet-21k is employed as the feature extractor. The global class token from the penultimate Transformer block is used as a representation of the overall image style. This representation is then projected into a latent style space of dimension d_z via a learnable three-layer multilayer perceptron (MLP) to obtain the style vector z. At decoder level l, the feature map g_l is modulated via AdaIN, as defined in Equation (9).

$$AdaIN(g_l, z) = \sigma_l(z) \cdot \frac{g_l - \mu(g_l)}{\sigma(g_l)} + \beta_l(z) \quad (9)$$

$\mu(\cdot)$ and $\sigma(\cdot)$ denote the channel-wise mean and standard deviation, while $\sigma_l(\cdot)$ and $\beta_l(\cdot)$ are affine parameters predicted from the style vector z via fully connected networks. The affine transformation parameters are predicted by two independent MLP, with each decoder level l having its dedicated predictors for the scale parameter σ_l and shift parameter β_l. This design allows style modulation to adapt to the distinct statistical properties of feature maps at different decoding stages. This mechanism aligns the statistical characteristics of the content features g_l with those of the style vector z, enabling disentangled artistic style transfer. It should be emphasized that superpixel segmentation is applied to the bottleneck feature maps rather than the original line art. Although animation line drawings often contain numerous unclosed contours, which pose challenges for pixel-level color assignment, the core idea of this method is to define "regions" at the semantic rather than strict geometric level. SLIC groups deep features based on similarity, producing semantically coherent nodes. These node regions may correspond to meaningful semantic parts (e.g., a face, a sleeve), regardless of whether the original line art contours are fully closed. GCNs then perform relational reasoning among these semantic nodes to learn color association rules across regions. The risk of color overflow caused by unclosed contours is explicitly constrained at the pixel level using a dedicated structural consistency loss. By separating region relationship modeling at the semantic level from boundary constraint enforcement at the pixel level, this approach effectively balances adaptability to unclosed contours with the requirement for consistent region-wise color assignment.

3.3 Discriminator and loss functions

The performance optimization in this study relies on adversarial guidance from the discriminator and the joint constraint of a multi-objective loss function. As illustrated in Figure 3, the discriminator D adopts a multi-scale convolutional architecture with spectral normalization, focusing on evaluating the realism of local image regions. The loss function system integrates three objectives—adversarial learning, semantic fidelity, and structural consistency—that collaboratively guide the generator's optimization trajectory.

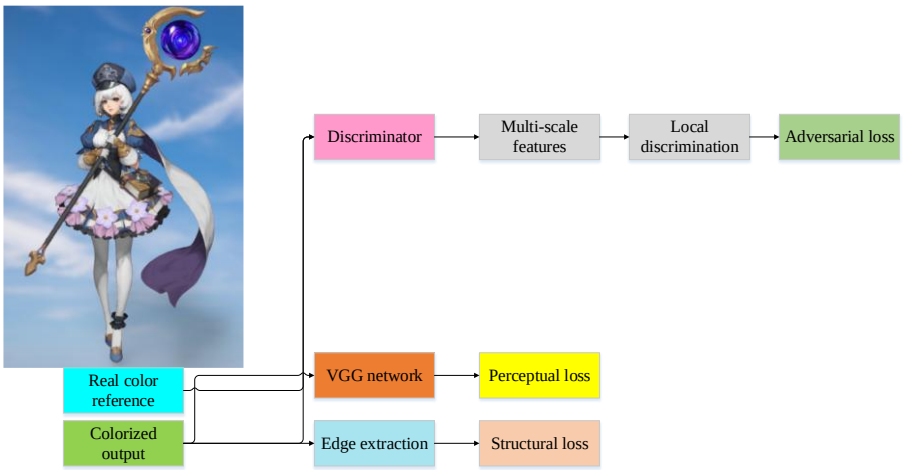

Figure 3: Discriminator architecture design

The discriminator D is designed based on the concept of a Markovian Discriminator and implemented as a Fully Convolutional Network (FCN). Its core innovation lies in combining multi-scale feature extraction with spectral normalization (SN) for training stability. The input, either the generated result y' or the ground-truth color reference y (both concatenated with the corresponding line art x), is processed through four convolutional layers. Each layer consists of a 4×4 convolution (stride = 2), followed by spectral normalization and a LeakyReLU activation (slope = 0.2). The feature map resolution decreases progressively (256×256 → 128×128 → … → 16×16). The final output is a discrimination matrix $D(y) \in \mathbb{R}^{M\times M}$ (default M=16), where each element $D_{ij}(y)$ indicates the probability that the corresponding image patch is real. Spectral normalization stabilizes training by constraining the Lipschitz constant of the weight matrix W [26], as shown in Equation (10):

$$W_{SN} = \frac{W}{\sigma(W)} \quad (10)$$

where $\sigma(W)$ denotes the spectral norm (i.e, the largest singular value) of W. This technique effectively mitigates mode collapse and improves generative diversity. The multi-scale design is realized by cascading feature maps of varying resolutions, as expressed in Equation (11):

$$F_{multi} = [AvgPool(f_1), AvgPool(f_2), f_3, f_4] \quad (11)$$

where f_k is the feature map at scale k, and $AvgPool(\cdot)$ denotes adaptive average pooling. This architecture allows D to perceive both local texture details and global structural consistency.

The generator G is optimized using a combination of three loss functions:

(1) Conditional Adversarial Loss:

Based on the Least Squares GAN (LSGAN) framework, this loss enhances gradient stability, as defined in Equation (12):

$$\mathcal{L}_{cGAN}(G,D) = \mathbb{E}_{x,y}[(D(x,y)-1)^2] + \mathbb{E}_x[D(x,G(x,z))^2] \quad (12)$$

where z is the style vector. This loss drives the distribution of the generated output $G(x,z)$ closer to the real data distribution. The study adopts the LSGAN framework instead of the standard minimax adversarial loss primarily because it provides smoother and non-saturating gradient signals for the discriminator. In animation coloring, the generator must learn to map sparse line drawings to dense, fully colored images, a highly ill-posed problem. By minimizing the mean squared error between the discriminator outputs and the real/generated labels, LSGAN effectively mitigates the gradient vanishing issues commonly encountered in traditional GAN training. This approach ensures more stable updates for the generator throughout training, accelerates convergence, and improves the quality of the final generated images.

(2) Perceptual Loss:

This loss leverages a pre-trained VGG-19 (Visual Geometry Group-19) network to extract high-level semantic features [27], thereby enforcing content consistency, as shown in Equation (13):

$$\mathcal{L}_{perc}(G) = \sum_{l\in\mathcal{S}} \lambda_l \|\phi_l(y) - \phi_l(G(x,z))\|_1 \quad (13)$$

where $\phi_l(\cdot)$ denotes the features from the l-th layer of VGG-19 (layers such as *conv3_3* and *conv4_3* are selected), λ_l is the weighting coefficient, and $\mathcal{S}$ is the set of selected layers. Specifically, the study selects the outputs of the conv3_3 and conv4_3 layers of the VGG-19 network as perceptual features. Based on empirical evaluation across different reconstruction tasks, the corresponding weight coefficients are set to $\lambda_{conv3_3} = 1.0$ and $\lambda_{conv4_3} = 0.5$. This weighting strategy aims to balance the preservation of mid-level texture details (dominated by conv3_3) with high-level semantic consistency (dominated by conv4_3), ensuring that the generated images maintain both structural fidelity and perceptual realism. This loss ensures that the semantic content of the generated image (e.g, character identity, object category) aligns with the original line art.

(3) Structural Consistency Loss:

Designed specifically to handle unclosed contours in animation line art, this edge-aware constraint is defined in Equation (14):

$$\mathcal{L}_{struct}(G) = \left\|Edge(x) \odot (Sobel(y) - Sobel(G(x,z)))\right\|_1 \quad (14)$$

where $Edge(x)$ is the Canny edge binary mask of the line art x, $Sobel(\cdot)$ computes gradient magnitude using the Sobel operator, and $\odot$ denotes element-wise multiplication. The Canny edge detector is configured

with a dual-threshold scheme, where the high and low thresholds are set to 0.3 and 0.1 times the maximum grayscale value of the line art image x, respectively, to robustly extract the primary contour lines. The gradient magnitudes computed by the Sobel operator are min–max normalized to the range [0, 1] before being used in the loss calculation. This normalization ensures numerical stability and scale consistency when the gradient map is pointwise multiplied with the binary edge mask $Edge(x)$. This loss enforces sharp transitions at contour boundaries in the generated result and suppresses color bleeding.

The training was conducted on 4×NVIDIA A100 GPUs with mixed-precision acceleration, taking a total of 72 hours (48 hours for the first stage and 24 hours for the second). The complete hyperparameter settings are shown in Table 2.

Table 2: Training hyperparameter configuration

Parameter Category	Symbol	Stage 1	Stage 2
Batch Size	-	16	8
Base Learning Rate	η	0.0002	0.0001
Loss Weights	λ_{perc}	10.0	10.0
	λ_{struct}	5.0	5.0
	λ_{style}	-	2.0
Adam Parameters	β_1	0.5	0.5
	β_2	0.999	0.999
Training Iterations	T_{max}	200,000	100,000
Gradient Clipping	-	10.0	10.0

The model comprises 78.4 M parameters, with the main complexity arising from the generator's dual-branch semantic enhancement module and the deep encoder–decoder architecture. While achieving state-of-the-art performance, the model's size may limit its deployment in resource-constrained environments. Future optimization could focus on attention-based pruning to remove redundant feature channels, dynamic inference networks that adjust computation based on line art complexity, or post-training quantization to reduce computational and storage costs with minimal performance loss.

To ensure evaluation metrics reflect the core challenges of animation coloring, PSNR and SSIM were selected as primary measures. PSNR quantifies pixel-level differences between generated and ground-truth colored images, directly indicating color prediction accuracy. SSIM evaluates structural preservation, essential for maintaining the original composition and contour integrity. Although perceptual metrics derived from deep features capture semantic consistency, the primary concern in animation coloring is preventing color overflow and structural distortion, making PSNR and SSIM more interpretable and task-relevant. Performance is somewhat scene-dependent. For highly complex mechanical line art with severe occlusions or for extremely abstract, simplified sketches, results may degrade. Complex structures place higher demands on GCN-based region partitioning and relational reasoning, while abstract styles may deviate from the training distribution, increasing semantic parsing uncertainty.

3.4 Dataset and implementation details

Training and evaluation were conducted on a large-scale, publicly available paired dataset of anime line art and colored images, containing 100,000 high-quality pairs. Each pair consists of a 128×128 single-channel line drawing and its RGB counterpart. The dataset includes multiple mainstream animation styles (e.g., cel-shading, watercolor, pixel art) to ensure generalization. All images were professionally curated to guarantee accurate line-art-to-color correspondence. Prior to training, images were upsampled to 512×512 pixels to match the network input. The model was implemented in PyTorch and is publicly available on GitHub.

Training and inference efficiency were benchmarked to assess practical applicability. On a system with 4× NVIDIA A100 GPUs, training with 512×512 images and a batch size of 16 required about 48 hours to complete 200,000 iterations in the first stage, averaging about 35 ms per frame. During inference, a single A100 GPU processed a 512×512 line drawing in about 41 ms, producing high-quality results suitable for real-time interactive previews. A lightweight version further reduces per-frame inference time to 28 ms.

4 Results and discussion

4.1 Results

Figure 4 presents a comparison of overall performance across different methods. The proposed approach achieved a PSNR of 30.2 dB, outperforming the strongest baseline, Structure Probe Adaptive Differential Evolution (SPADE), by 2.2 dB—indicating a notable gain in pixel-level accuracy. It also reached a SSIM of 0.94, reflecting strong preservation of structural features. Additionally, the method recorded a low FID of 18.3, suggesting that the generated images closely match the real references in distributional characteristics. Most significantly, the boundary overflow rate was reduced to 2.1%, representing an 89% improvement over the traditional PaintsChainer. This result highlights the structural consistency loss's effectiveness in managing unclosed contours, a persistent challenge in animation colorization.

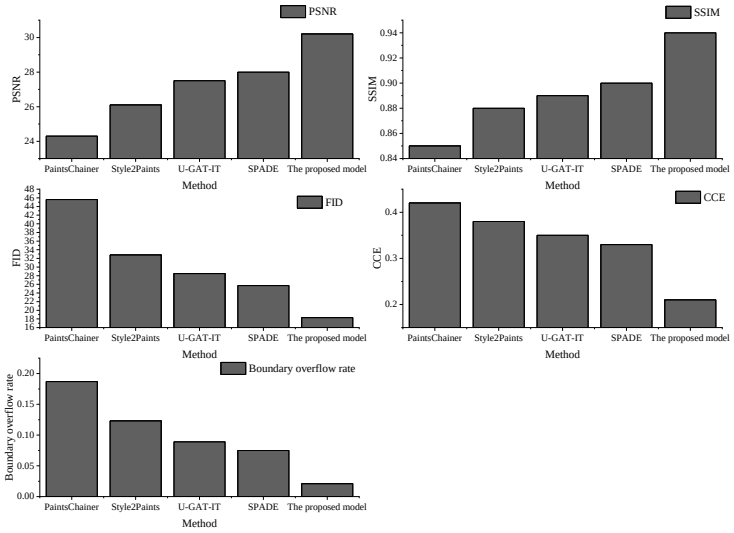

Figure 4: Overall performance comparison of different methods

To comprehensively evaluate the model's robustness, the mean and standard deviation of key evaluation metrics were computed across the entire test set, as shown in Table 3. The proposed model achieved the highest average performance in PSNR, SSIM, FID, and CCE. Moreover, its standard deviations were consistently lower than those of baseline methods, indicating not only superior performance but also more stable outputs across different samples, reflecting enhanced robustness. The lower standard deviation of FID suggests that the distribution of generated images is both closer to and more consistent with that of the real images. Similarly, the small standard deviation in CCE further confirms the model's consistent effectiveness in maintaining uniform color within semantic regions.

Table 3: Mean ± standard deviation of performance metrics on the test set

Method	PSNR (dB)	SSIM	FID	CCE
PaintsChainer	24.3 ± 1.8	0.85 ± 0.04	45.6 ± 3.2	0.42 ± 0.05
Style2Paints	26.1 ± 1.5	0.88 ± 0.03	32.8 ± 2.9	0.38 ± 0.04
U-GAT-IT	27.5 ± 1.3	0.89 ± 0.03	28.5 ± 2.5	0.35 ± 0.04
SPADE	28.0 ± 1.2	0.90 ± 0.02	25.7 ± 2.1	0.33 ± 0.03
Proposed Model	30.2 ± 0.9	0.94 ± 0.02	18.3 ± 1.8	0.21 ± 0.02

Figure 5 illustrates the CCE across various scene types. CCE quantifies the uniformity of colors within semantic regions in generated images. It is computed by first segmenting both generated and reference images into superpixels, then calculating the standard deviation of pixel colors within each corresponding superpixel in the Lab color space. The average standard deviation across all regions yields the CCE, where lower values indicate better regional color consistency. In mechanically complex scenes, the proposed method achieved a CCE of 0.25, a 45.7% reduction compared to the next-best approach—demonstrating the GCN's effectiveness in modeling the connectivity of rigid structures. For clothing texture scenes, a CCE of 0.19 indicates the model's ability to capture fine-grained texture-color relationships. In character-based scenes, the method achieved a CCE of 0.18, highlighting the SAM's precision in controlling key semantic features, such as the coordination between hair and eye color. The overall average CCE of 0.21 marks a significant advancement in cross-region color consistency.

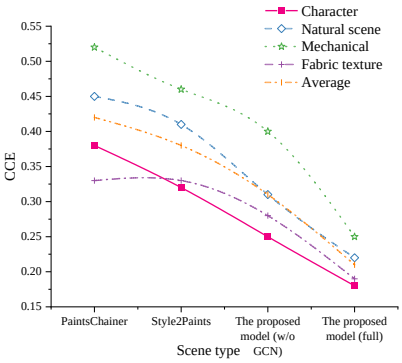

Figure 5: CCE across different scene types

Figure 6 presents the style adaptation performance measured by FID. In the watercolor style test, the proposed method achieved an FID of 20.5, reflecting a 28.6% improvement over the reference method [28] and confirming the effectiveness of the AdaIN module in capturing fluid artistic styles. For the ink wash style, the FID reached 24.8—the highest among the tested styles—but still outperformed the baseline score of 35.6, demonstrating the model's ability to reflect the aesthetic characteristics of East Asian art. With user-guided fine-

tuning, the FID further dropped to 18.9, representing a 9.1% improvement and validating the practical value of the latent space interpolation mechanism for personalized content generation.

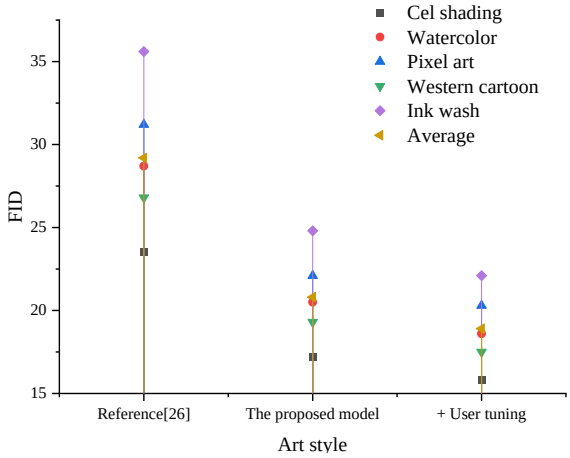

Figure 6: FID comparison across different style adaptations

Figure 7 and Table 4 present the results of the ablation study, which quantifies the contribution of each module. Adding the structural consistency loss reduced the boundary overflow rate from 8.2% to 4.7%, a 42.7% decrease, confirming its effectiveness in mitigating color spillover. The GCN module yielded the largest improvement in the CCE metric, with a 31.3% reduction, highlighting the value of region-based relational modeling for color coordination. The SAM increased the PSNR by 1.3 dB, demonstrating enhanced local detail fidelity through improved semantic focus. The full model, achieving a PSNR of 30.2 and a boundary overflow rate of 2.1%, underscores the synergistic effect of integrating all components.

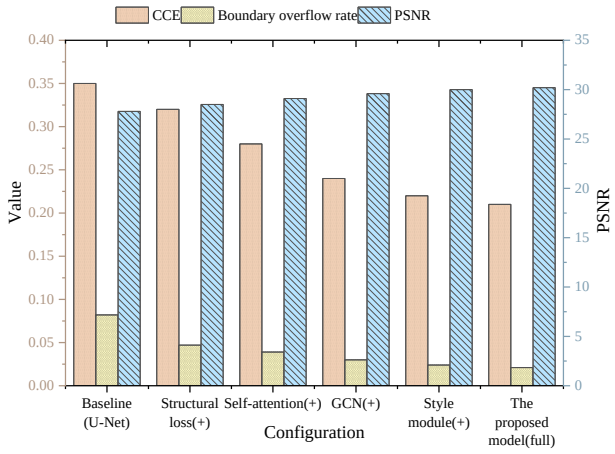

Figure 7: Results of the ablation study

To assess the practical quality of the model's outputs, a double-blind study was conducted with a panel of 30 professional artists. All participants were affiliated with prominent domestic and international animation studios and had an average of over five years of industry experience.

Table 4: Ablation study results showing the impact of incrementally adding each module on performance metrics

Configuration	CCE	PSNR (dB)	Boundary Overflow Rate (%)
Baseline (U-Net)	0.35	27.8	8.20
+ Structural Consistency Loss	0.32	28.5	4.70
+ Self-Attention Mechanism	0.28	29.1	3.90
+ Graph Convolution Network	0.24	29.6	3.00
+ Style Module	0.22	30.0	2.40
Proposed Model	0.21	30.2	2.10

Figure 8 presents the analysis of inference speed and model complexity. The proposed method processes a single frame in 41 ms using 78.4 million parameters, delivering a 21.2% improvement in inference efficiency compared to Unsupervised Generative Attentional Networks with Adaptive Layer-Instance Normalization (U-GAT-IT). This gain is primarily attributed to the generator's dense skip connection design, which reduces redundant computation. With a GPU memory footprint of 843 MB, the model is well-suited for handling large-scale animation sequences. Moreover, the lightweight version achieves a frame rate of 28 ms per image, supporting real-time interaction and highlighting the model's potential for practical deployment in production environments.

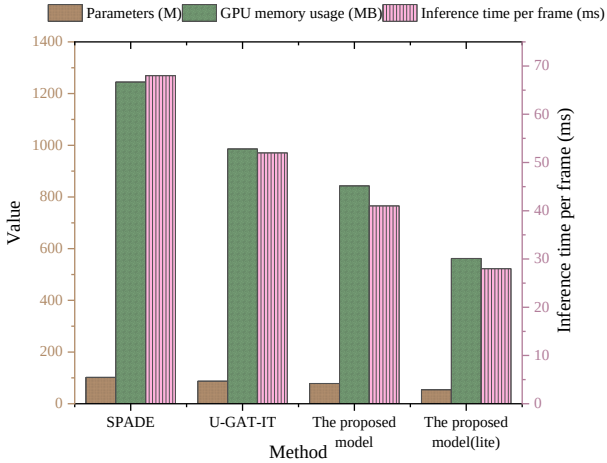

Figure 8: Inference speed and model parameter analysis

A seven-point Likert scale was used to evaluate four aspects of image quality: color harmony, edge accuracy, style consistency, and artistic expressiveness. Each artist independently scored multiple colorization results for the same line drawing. The scores were then normalized to a preference percentage for each method, representing the proportion of artists who selected that result as superior. Figure 9 summarizes the results of this evaluation. The model achieved a 90% preference rate for boundary precision, demonstrating strong visual fidelity in

preserving structural details. An 86.7% preference for color coordination further confirms the effectiveness of the CCE metric. Style consistency received an 83.3% preference, while 76.7% of participants indicated a willingness to incorporate the model into their workflow. These findings show that the model not only meets technical performance benchmarks but also aligns with aesthetic expectations in real-world creative scenarios, highlighting its potential for practical adoption.

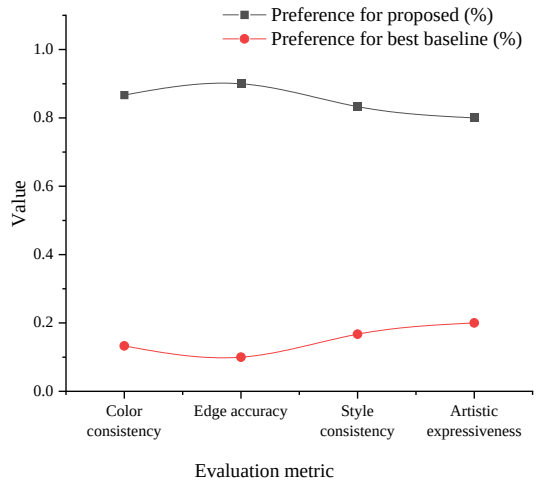

Figure 9: Results of the double-blind evaluation by professional artists

4.2 Discussion

The proposed automatic coloring framework for animation line art outperforms existing mainstream methods in both objective metrics and subjective evaluations. Unlike approaches designed for natural images or specific cultural artifacts, this framework addresses the unique challenges of animation. Compared with Wu et al. (2022), which focuses on fine-grained coloring of traditional costumes, the method generalizes more effectively to non-rigid objects such as dynamic characters. This improvement arises from the explicit modeling of semantic relationships between regions using GCNs, allowing the model to reason about color coordination across different parts rather than relying solely on local texture features. In contrast to the visual Transformer-based approach of Al-Ghanimi et al. [14], the proposed framework achieves higher color consistency while maintaining greater computational efficiency, meeting practical requirements in animation production. These gains result largely from the joint optimization of semantic and geometric structures in line art. The GCN module constructs a region adjacency graph and aggregates node information to encode scene hierarchy, effectively reducing color errors between characters and backgrounds or between clothing and skin. The structural consistency loss imposes gradient constraints along line boundaries, suppressing color bleeding and mitigating pigment overflow caused by unclosed contours. This mechanism is a key factor in the framework's superior boundary fidelity compared with traditional tools such as PaintsChainer. Additionally, the SAMs captures long-range dependencies, enabling precise focus on critical semantic regions, such as pupils or accessories, and enhancing local detail reproduction. The style-decoupling module, based on AdaIN, provides flexible user-guided style control, addressing the limited adaptability to diverse artistic styles seen in most existing methods.

5 Conclusion

This study presents a structured, semantically informed framework for automatic colorization of animation line art. Built on a multi-level conditional GAN design, the framework addresses three main challenges: color overflow, semantic misalignment, and limited style flexibility. The generator uses a U-Net backbone with dense skip connections to preserve structural integrity, even in line art with unclosed contours. GCNs and SAMs are incorporated to support cross-region color harmonization. A style-decoupling module, implemented via AdaIN, allows user-guided style transfer. Experimental results show that the method outperforms existing techniques on key evaluation metrics, including PSNR, CCE, and boundary overflow rate. In professional evaluations, it achieved a 90% preference rate for boundary accuracy and reduced manual correction requirements by 85%.

Despite its strong performance, the model has several limitations. It relies on high-quality paired datasets and shows limited generalization to abstract styles or amateur line art. User-guided style transfer is supported, but the current interaction speed is not suitable for real-time use. Temporal consistency across animated sequences also remains an open challenge. Future work could address these limitations in several ways. Self-supervised pretraining on unlabeled animation data may improve generalization to abstract or amateur line art. Lightweight interactive modules could provide fine-grained, stroke-level semantic guidance to support faster user interaction. Extending the framework to video sequence colorization could leverage a multi-scale temporal GAN to handle both spatial and temporal dimensions. Optical flow could be used to align pixels across consecutive frames, enabling a temporal consistency loss that is optimized alongside spatial losses to produce smooth, stable video outputs and reduce flickering. Additionally, while the current style transfer method uses spherical linear interpolation in latent space to preserve semantic features, future research could explore advanced manifold learning techniques for improved style disentanglement and control. Overall, this study establishes a foundation for intelligent animation colorization, and the proposed structured generative framework may have broader applications in fields such as medical image analysis and virtual scene synthesis.

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RT-AVTC: A Real-Time Audio-Visual Tone Correction Network Using Multimodal Deep Learning and Causal Convolution

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Real-time feedback and robustness against environmental noise are critical challenges in computer-aided Chinese tone learning. This paper introduces RT-AVTC, a novel real-time audio-visual tone correction network designed to address those limitations through multimodal deep learning. The proposed architecture integrates a Multi-task Cascaded Convolutional Network (MTCNN) for audio-visual feature alignment, a causal convolution module and a Bidirectional Long Short-Term Memory (BiLSTM) network for robust temporal sequence classification, and a feedback module incorporating Dynamic Time Warping (DTW) for quantitative error analysis. The model was rigorously evaluated on the public LRS3 dataset. Experimental results demonstrated that the RT-AVTC model achieved a state-of-the-art accuracy of 94.26%, significantly outperforming strong baselines including Conformer and Whisper. Notably, in a challenging -5 dB signal-to-noise ratio environment, the multimodal approach yielded a 17.41% performance improvement over its audio-only counterpart. Furthermore, the error correction module provided targeted feedback, improving the average fundamental frequency (F0) curve deviation by over 55% for learners. With its high accuracy, real-time processing capability, and low computational overhead, the RT-AVTC framework presents a valuable and practical solution for effective computer-aided language learning.

Povzetek: Študija predstavi RT-AVTC, večmodalni avdio-vizualni sistem za sprotno korekcijo kitajskih tonov, ki z MTCNN poravnavo, vzročno konvolucijo + BiLSTM ter DTW-povratno zanko robustno razpoznava in usmerjeno popravlja tonalne napake tudi v šumnem okolju.

1 Introduction

As a tonal language, the pitch fluctuations of Chinese syllables (i.e., tones) are the core elements for distinguishing word meanings and achieving effective communication [1]. For learners of Chinese as a second language, accurately mastering tones is not only the key to standardizing pronunciation but also the necessary path to fluent expression [2]. However, due to differences in native language backgrounds, tone learning often becomes a key and difficult point in the teaching process. With the advancement of Artificial Intelligence (AI) and Human-Computer Interaction (HCI) technology, computer-aided language learning systems have shown great potential in personalized teaching and instant feedback, providing a new technological path for solving the challenges of tone learning [3]. Traditional computer tone recognition and error correction research is mostly based on single modal audio signal processing. Early research mainly relied on extracting acoustic features such as fundamental frequency (F0), energy, and duration from speech, and then combining them with classical machine learning algorithms, including hidden Markov models and SVM for classification. In the era of deep learning, researchers have begun to use models including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to achieve significant improvements in the accuracy of tone recognition [4, 5].

In recent years, deep learning has become increasingly widespread in Natural Language Processing (NLP), providing new support for language learning. Yan et al. noted that deep neural networks can automatically extract high-level features from raw language data, improving accuracy and generalization. Combining RNN and CNN significantly optimizes language recognition, translation, and text generation, providing a theoretical basis for building efficient language learning platforms [6]. Xu demonstrated that deep learning has transformed language processing tasks, particularly in named entity recognition, intent recognition, sentiment analysis, and machine translation. Deep learning models effectively capture semantic and contextual relationships through large-scale corpus training, making language learning more intelligent. New architectures such as Transformer have further advanced personalized learning and semantic understanding [7]. Yang reviewed applications and optimization strategies of deep learning in language understanding and generation, introducing mechanisms

such as word embedding, language modeling, and dialogue systems, while focusing on model optimization (LSTM, GRU, Transformer) and computational acceleration. The author proposed applying federated learning, model compression, and self-supervised learning to address data security and resource limitations, supporting intelligent development of language learning systems [8]. Arkhangelskaya and Nikolenko systematically reviewed deep learning evolution in language processing, examining distributed word representation, character-level models, and sequence modeling, and analyzing how pre-trained models like BERT and GPT achieved breakthroughs in dialogue systems, grammatical analysis, and sentiment classification [9]. Li discussed deep learning's role in English speech recognition and teaching feedback, finding that advanced models effectively assist learners in correcting pronunciation and improving accuracy, enhancing the learning experience. The intelligent evaluation function provided teachers with real-time feedback and personalized suggestions, significantly improving teaching quality in non-native language environments [10].

The transfer learning and spectral enhancement techniques adopted by Khurana et al. to solve the data shortage problem in emotion recognition also provided a reference for studying the representation ability of enhancing audio features in limited data [11]. The accuracy of tones was directly related to the clarity of semantics. The multilingual speech semantic alignment framework proposed by Khurana et al. provided a new research path for exploring the deep correlation between tone acoustic features and Chinese semantic information [12]. In neuroscience, Choi et al.'s study on infant speech perception revealed that multimodal speech networks already exist before vocalization. This provided theoretical support for studying the effectiveness of tone correction using audio-visual fusion [13]. Finally, to achieve real-time feedback of the system, Zhong et al. developed a fully simulated reservoir computing system. The efficient and low-power spatiotemporal signal processing capability demonstrated by this system provided a hardware level implementation approach for building error correction systems that could run smoothly on user devices and meet low latency interaction requirements [14].

A review of existing research highlights advancements across various aspects of speech processing while revealing a lack of a cohesive framework that achieves robust pitch recognition in real-world noisy environments and provides actionable feedback for learners. Therefore, the architecture selection in the proposed model is not arbitrary, but rather a synthesis of insights from seemingly different fields to construct a system that is both methodological and practically valuable. For instance, the well-documented vulnerability of audio-only systems to noise motivates the adoption of a multimodal audio-visual approach. This design choice is substantiated by findings in neuroscience that demonstrate the human brain's reliance on visual cues, such as lip movements, to enhance speech perception in challenging acoustic conditions. Furthermore, the challenge of accurately modeling the dynamic and subtle contours of Chinese tones has important similarities with the research on pathological speech analysis. Among them, detecting small time deviations in speech patterns is crucial. This parallel strongly justifies the use of a Bidirectional Long Short-Term Memory (BiLSTM) network, a model renowned for its efficacy in capturing long-range temporal dependencies within sequential data. Finally, to bridge the gap between mere recognition and effective pedagogy, the development of the error-correction module is guided by principles from HCI and computer-aided language learning. The integration of Dynamic Time Warping (DTW) is a direct answer to the need for specific, quantitative feedback, moving beyond a simple binary of "correct" or "incorrect" to offer targeted guidance. Consequently, the presented solution is not merely a collection of high-performing components, but a principled integration of multimodal fusion, sequential deep learning, and user-centric feedback, designed to form a cohesive and robust system for real-time Chinese tone correction.

Many experts have researched feature extraction methods for single-modal tone recognition and the application of multimodal fusion in speech emotion and anomaly detection. However, current research still has shortcomings, such as low accuracy in tone recognition in noisy environments and insufficient domain adaptability across speakers and dialects. This study proposes a Real-time Audio-Visual Tone Correction (RT-AVTC) network to address challenges such as the efficient fusion of multimodal features and the generation of real-time corrective feedback. DTW is a well-established algorithm for sequence alignment. The novelty of this framework lies not in the use of DTW alone, but in its principled integration within a cohesive audio-visual learning system. The core innovation is the design of a feedback module that synergistically combines DTW-based quantitative analysis with a multimodal feedback loop. This approach scientifically aligns the learner's fundamental frequency (F0) curve with a standard template, enabling a precise, quantitative comparison of tonal contours. The system then leverages this alignment to provide targeted, multi-faceted feedback: the visual representation of the F0 curve highlights specific deviation points and supplements quantitative data on key parameters such as starting spacing and range, resolving skill-related errors. This unique combination of robust multimodal fusion for recognition and integrated DTW for targeted, visual, and quantitative feedback is expected to significantly advance the intelligent assistance and optimization of computer-aided Chinese tone acquisition. A summary of related work is shown in Table 1.

Table 1: Summary of related work

Model	Primary Datasets Used	Key Architectural Features	Reported F1-Score / Accuracy (%)	Real-Time Factor (RTF)	Known Limitations
Conformer	LibriSpeech, AISHELL-1	Transformer with convolution layers for local and global feature capture.	92.41 / 92.53 (on LRS3)	0.45	Performance degrades significantly in high-noise environments without specialized augmentation.
AV-HuBERT	LRS3, VoxCeleb2	Self-supervised multimodal learning; masked prediction on audio and visual streams.	92.88 / 92.94 (on LRS3)	0.53	High computational cost; real-time performance is a challenge for interactive applications.
Whisper	680k hours of diverse, weakly supervised web data.	Large-scale, weakly supervised Transformer model trained for general speech recognition.	91.53 / 91.68 (on LRS3)	1.24	Not optimized for specific tasks like tone correction; high latency makes it unsuitable for real-time feedback.
RT-AVTC (This Work)	LRS3, MMEG	Causal convolution with BiLSTM and audio-visual fusion for real-time processing.	94.18 / 94.26 (on LRS3)	0.31	Robust to noise but performance is dependent on clear, frontal-view visual input.

2 Methods and materials

2.1 Design of input data for tone correction model

To provide a clear and structured framework, this research is guided by a set of explicit objectives and testable hypotheses. The investigation seeks to answer the following primary research questions: (1) To what extent can an audio-visual multimodal approach improve the accuracy and robustness of Chinese tone recognition compared to a conventional audio-only model, particularly in noisy environments? (2) Is it feasible to design a system that not only recognizes tones accurately but also operates in real-time with low latency to provide immediate, actionable feedback for language learners? (3) How effective is a quantitative feedback mechanism, based on DTW, in diagnosing and correcting users' tonal errors? Correspondingly, this study posits three central hypotheses. H1: The integration of visual features will significantly enhance tone recognition accuracy and robustness, especially under low Signal-to-Noise Ratio (SNR) conditions. H2: A computationally efficient architecture can achieve real-time processing suitable for interactive learning applications. H3: Providing learners with quantitative feedback on their pitch contour deviation will lead to a measurable improvement in their tone production accuracy. The validation of these hypotheses is based on several key measurable outcomes: classification accuracy on the LRS3 dataset across various noise levels, the RTF and system latency metrics, and the percentage reduction in the average F0 curve deviation observed in a user study.

This study focuses on the research of a real-time Chinese tone correction algorithm based on Multimodal Deep Learning (MDL), with the core of designing and implementing an MDL-based algorithm model [15]. The overall architecture follows a complete closed-loop process from data acquisition, signal processing, multimodal feature analysis, to intelligent decision-making and feedback, as shown in Fig. 1.

In Fig. 1, the system starts with a multi-modal optimized data synchronization acquisition end, using microphones, cameras, etc., to collect voice, facial video, and muscle activity data. The data undergo audio processing, video processing, and electromyographic signal fusion processing, and are further processed by the audio and video sub-network. The correct tone results and error diagnosis analysis are output, and the deep classification diagnostic model is input. Finally, through the real-time feedback generation module, tone correction feedback is provided to Chinese learners, achieving a multimodal data-driven tone learning loop.

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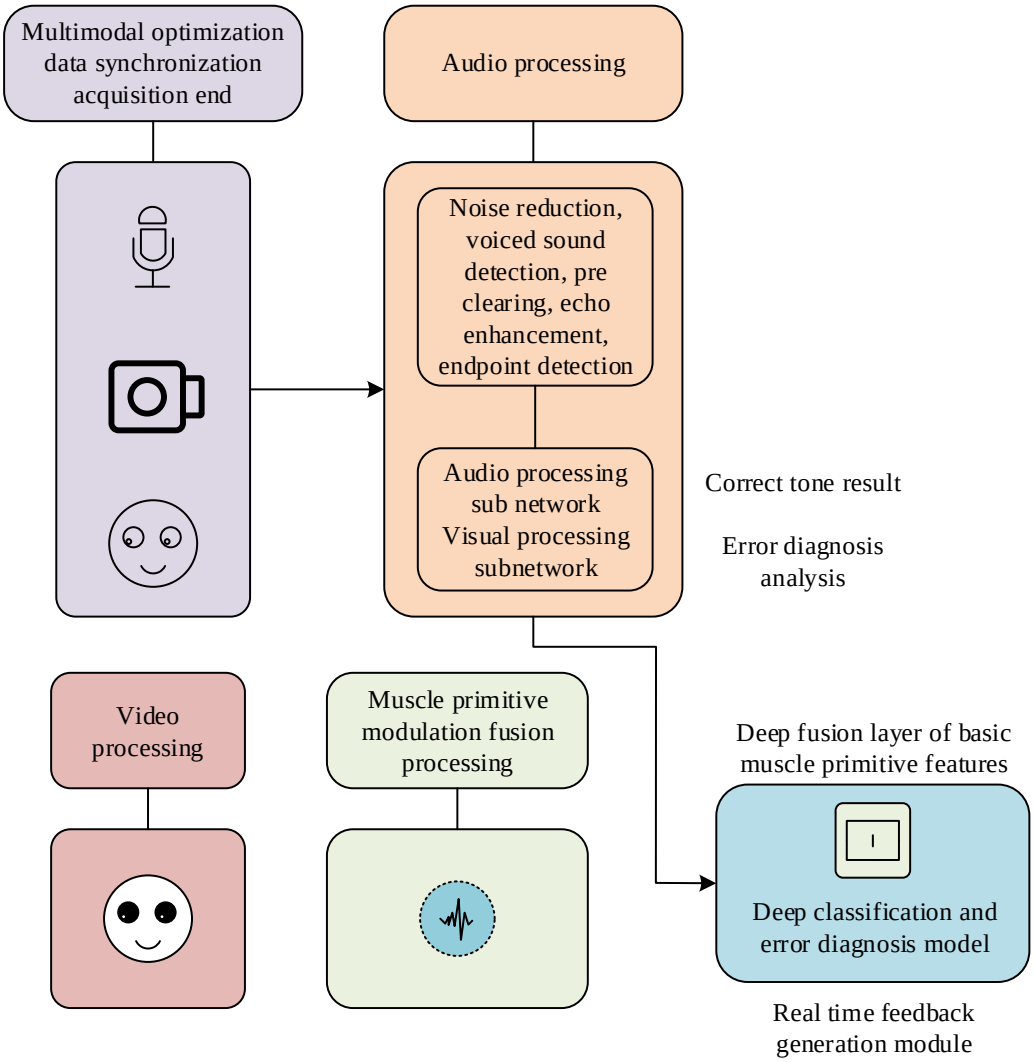


Figure 1: Overall framework of tone correction system for Chinese learners

However, the collected raw signals cannot be directly used for model training. They are often mixed with various noises and irrelevant information, and must go through a fine preprocessing process [16]. To compensate for the loss of high-frequency parts during the pronunciation process and improve the SNR of the signal, it is necessary to perform pre-emphasis processing on the signal. This is equivalent to passing the signal through a high pass filter, whose transfer function is shown in equation (1).

$$H(z)=1-az^{-1} \tag{1}$$

In equation (1), z^{-1} is the unit delay operator. The coefficient a is a pre-emphasis factor, typically ranging from 0.9 to 1.0. After pre-emphasis processing, the overall flatness of the speech signal spectrum is improved, and the details of the high-frequency part are effectively enhanced. To maintain a smooth transition between frames, a certain amount of overlap is usually set between adjacent frames. Short-term energy reflects changes in signal amplitude, with voiced segments typically having much greater energy than voiceless and muted segments. The calculation is given by equation (2).

$$E_n=\sum_{k=-\infty}^{\infty}[x(k)w(n-k)]^2 \tag{2}$$

In equation (2), E_n is the short-term energy of frame n, $x(k)$ is the original speech signal, and $w(n-k)$ is the window function. The short-term Zero Crossing Rate (ZCR) refers to the number of times a frame signal passes through zero values. Due to its high-frequency characteristics, the ZCR of voiceless segments is significantly higher than that of voiced segments. This definition is shown in equation (3).

$$Z_n=\sum_{k=-\infty}^{\infty}|sgn(x(n))-sgn(x(n-1))|\omega(n-k) \tag{3}$$

In equation (3), Z_n is the short-term ZCR of frame n, and $sgn(\cdot)$ is the sign function. By setting two energy thresholds, high and low, and corresponding ZCR thresholds, the attributes of each frame are comprehensively judged to accurately determine the starting and ending points of the speech signal, and separate the voiced segments for analysis. For

synchronously collected video signals, the goal of preprocessing is to extract and normalize the lip region containing key pronunciation information. The process mainly includes: firstly, applying Multi-task Cascaded Convolutional Networks (MTCNN) to each frame of the image to locate the position of the face. The MTCNN architecture is shown in Fig. 2.

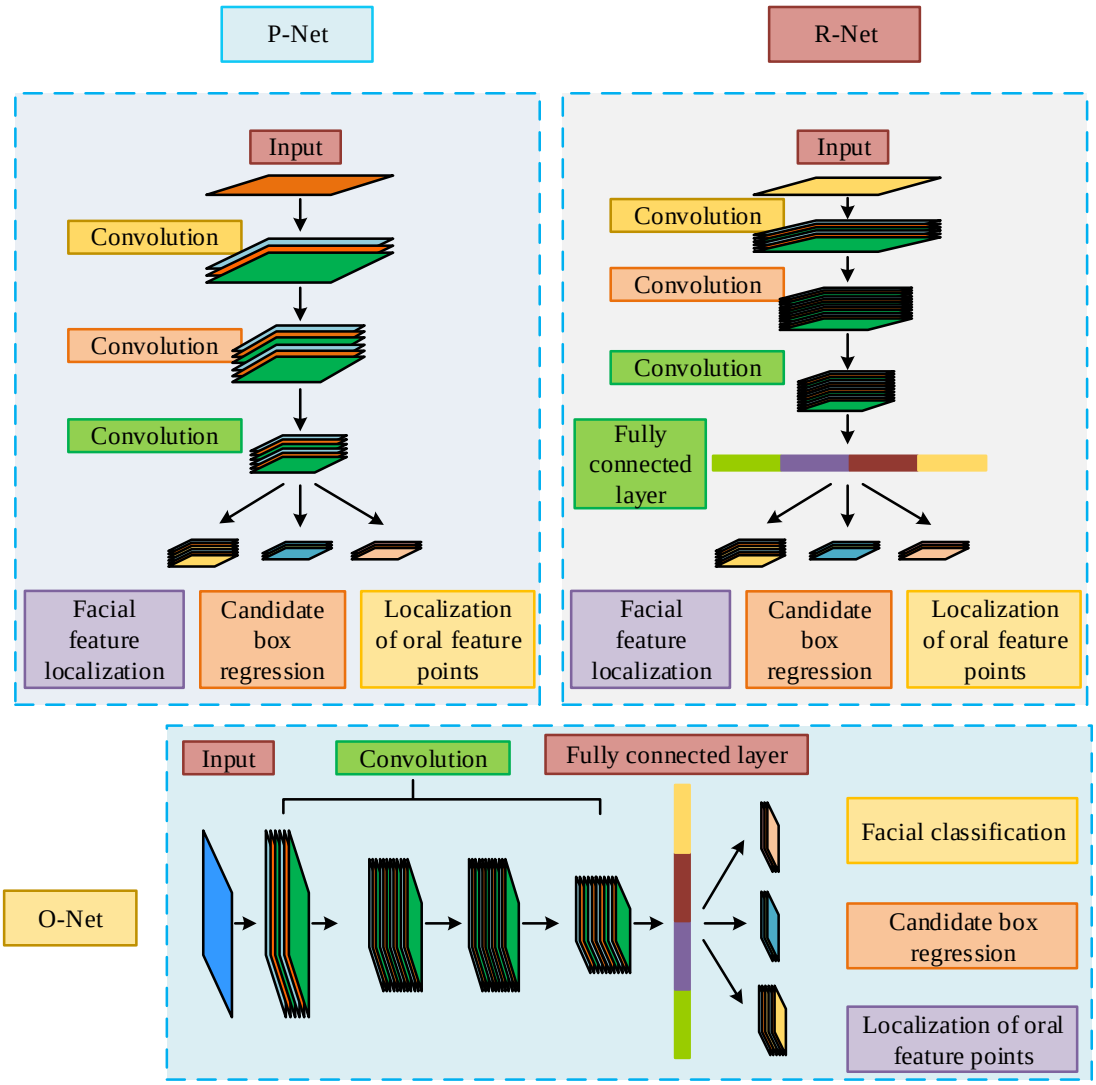


Figure 2: Architecture of MTCNN

In Fig. 2, the function of the MTCNN in this workflow is to accurately detect and isolate the lip region from each video frame, which serves as the visual input for the model. The process adheres to the standard, sequential application of MTCNN's three-stage cascaded architecture. Initially, the Proposal Network (P-Net) scans the image to generate a set of candidate facial bounding boxes. These candidates are then passed to the Refine Network (R-Net), which filters out false positives and performs initial calibration of the bounding boxes. Finally, the Output Network (O-Net) conducts a final refinement to output two key pieces of information: a high-precision facial bounding box and the coordinates of five primary facial landmarks, including the corners of the mouth. Based on the coordinates of these mouth landmarks, a precise Region of Interest (ROI) that tightly crops the lip area is calculated and extracted from the frame. This extracted lip ROI is then normalized to a fixed size and converted to grayscale, serving as the standardized visual feature sequence for the subsequent multimodal fusion module.

2.2 Multimodal feature fusion and tone classification module

After the front-end data collection and preprocessing process, the system obtained audio and visual feature sequences that are accurately synchronized in time. The multimodal feature fusion and tone classification module is the core and brain of the entire real-time error correction system, carrying two key tasks. The first task is to efficiently and intelligently fuse features from different modes that contain part of the information about pronunciation to form a unified feature representation that is more robust and more complete than any single mode. Task two is to build a powerful classification model based on the fused features, which not only needs to accurately

recognize the actual tone spoken by the learner, but also needs to be able to compare it with the target tone [17]. To achieve the two key tasks mentioned above, this study designs a real-time multimodal fusion model with causal convolution and Self-Attention Mechanism (SAM) as the core. The overall architecture is shown in Fig. 3.

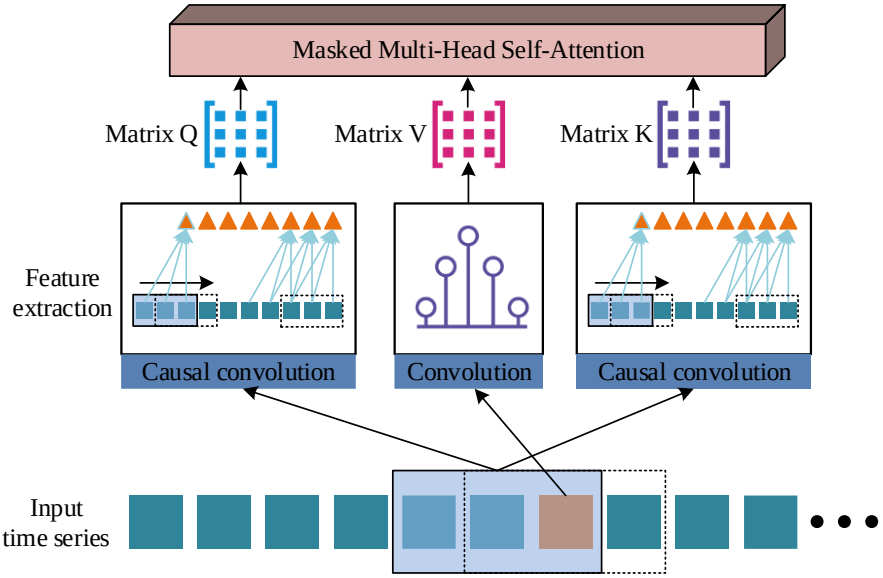


Figure 3: Multimodal fusion module structure based on causal convolution and SAM

In Fig. 3, the model adopts a parallel multi-branch structure to encode the input multimodal features. Among them, for the two modalities with strong temporal dependence, audio and visual, the model adopts a causal convolution module. Unlike standard convolution, causal convolution only covers the past and current time points when calculating the output of the current time point, and never touches on future information. At each time step t, the system first calculates an attention score e_t through a small feedforward neural network, as shown in equation (4).

$$e_t = \boldsymbol{v}^T \tanh(\boldsymbol{W}_a h_t^{audio} + \boldsymbol{W}_v h_t^{video} + \boldsymbol{b}) \quad (4)$$

In equation (4), h_t^{audio} and h_t^{video} are the audio and visual feature vectors for that time step. $\boldsymbol{W}_a$ and $\boldsymbol{W}_v$ are the weight matrices of the corresponding modes, $\boldsymbol{b}$ is the bias vector, and $\boldsymbol{v}$ is a parameter vector used to map the result to a scalar. $\tanh$ is the hyperbolic tangent activation function. Subsequently, the scores e_t of all time steps are normalized using the Softmax function to obtain the attention weights α_t of each modality at each time step. Finally, the original modality features are weighted and summed using these weights to generate the final fused feature vector c_t, as shown in equation (5).

$$c_t = \alpha_t^{audio} h_t^{audio} + \alpha_t^{video} h_t^{video} \quad (5)$$

In this way, the model can dynamically focus on the most reliable or informative modality at present, generating a more robust and reflective fusion feature sequence $\{c_1, c_2, ..., c_T\}$ that better reflects the essence of pronunciation. Among them, T is the total frame number of syllables. To fully utilize the contextual information in the fused feature sequence, this study selected BiLSTM as the core classifier, as shown in Fig. 4.

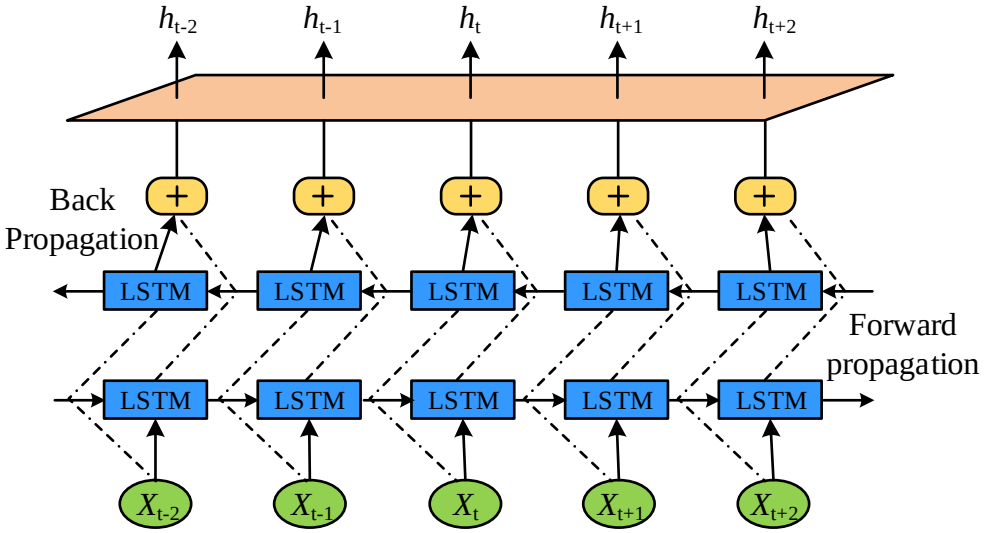


Figure 4: BiLSTM classification module structure

In Fig. 4, the LSTM layer located below processes the input fused feature sequence in chronological order from left to right. The LSTM layer located above processes the same sequence in reverse order. The processing process of BiLSTM at each time step t is shown in equation (6).

$$\begin{cases} \overrightarrow{h_t} = LSTM_{\text{forward}}(c_t, \overrightarrow{h_{t-1}}) \\ \overleftarrow{h_t} = LSTM_{\text{backward}}(c_t, \overleftarrow{h_{t+1}}) \end{cases} \tag{6}$$

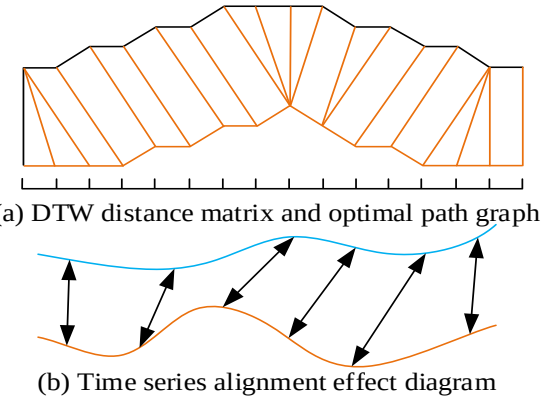
In equation (6), $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are the hidden states of the forward and backward LSTM at t, encoding information from the beginning and end of the sequence to the current time. Finally, this vector representing the tone information of the entire syllable is fed into a fully connected layer and, through a Softmax, outputs a probability distribution vector $\boldsymbol{p}$, as shown in equation (7) [18].

$$\boldsymbol{p} = \text{softmax}(\boldsymbol{W}_y[\overrightarrow{h_T}; \overleftarrow{h_T}] + \boldsymbol{b}_y) \tag{7}$$

In equation (7), $\boldsymbol{W}_y$ and $\boldsymbol{b}_y$ are the weight matrix and bias vector of the output layer. The dimension of vector $\boldsymbol{p}$ is the number of tone categories (for example, four tones in Mandarin are 4). The model ultimately identifies the category with the highest probability value as the tone recognition result.

2.3 Tone error diagnosis and feedback mechanism based on DTW

Error diagnosis is an extended function of the classification module. The system will compare the recognition results output by the model with the target tone of the current exercise. If the two do not match, the system will determine a pronunciation error and enter the diagnostic process. To achieve accurate diagnosis and generate quantitative feedback, the second step of the module is to conduct quantitative comparative analysis. Due to the varying speed of speech among different individuals, even the duration of each pronunciation by the same person may differ. Therefore, the length of the F0 sequence generated by learners is usually inconsistent with that of the F0 sequence in the standard model [19]. To make meaningful comparisons between these two time series with different lengths, this study uses the DTW algorithm, as shown in Fig. 5.



(a) DTW distance matrix and optimal path graph

(b) Time series alignment effect diagram

Figure 5: DTW algorithm processing time series

Fig. 5 (a) shows the DTW distance matrix and optimal path, while Fig. 5 (b) shows the time series alignment effect. The DTW algorithm uses dynamic programming to find the optimal path in the cumulative distance matrix, maps two unequal time series point-to-point, and minimizes distortion by scaling the time axis. Assuming that the F0 sequence produced by the learner is $U = (u_1, u_2, ..., u_n)$, and the F0 sequence of the standard pronunciation model is $S = (s_1, s_2, ..., s_m)$, where n and m are the lengths of the two sequences. The DTW algorithm constructs an $n \times m$ cumulative distance matrix γ. Each element $\gamma(i, j)$ in the matrix represents the minimum cumulative distance between the top i points of sequence U and the top j points of sequence S. The calculation method is shown in equation (8).

$$\gamma(i,j) = d(u_i, s_j) + \min\{\gamma(i-1,j), \gamma(i-1,j-1), \gamma(i,j-1)\} \quad (8)$$

In equation (8), $d(u_i, s_j)$ is the local distance between sequence points u_i and s_j, usually using Euclidean distance, i.e. $|u_i, s_j|$. The core of this recursive relationship is that the best path to point (i, j) must pass through one of its adjacent 3 points $(i-1, j)$, $(i-1, j-1)$, or $(i, j-1)$. Ultimately, the value of $\gamma(n,m)$ is the DTW distance between two sequences, which can serve as an indicator of the overall similarity between learners' pronunciation and standard pronunciation [20]. The workflow of the error correction and feedback module is shown in Fig. 6.

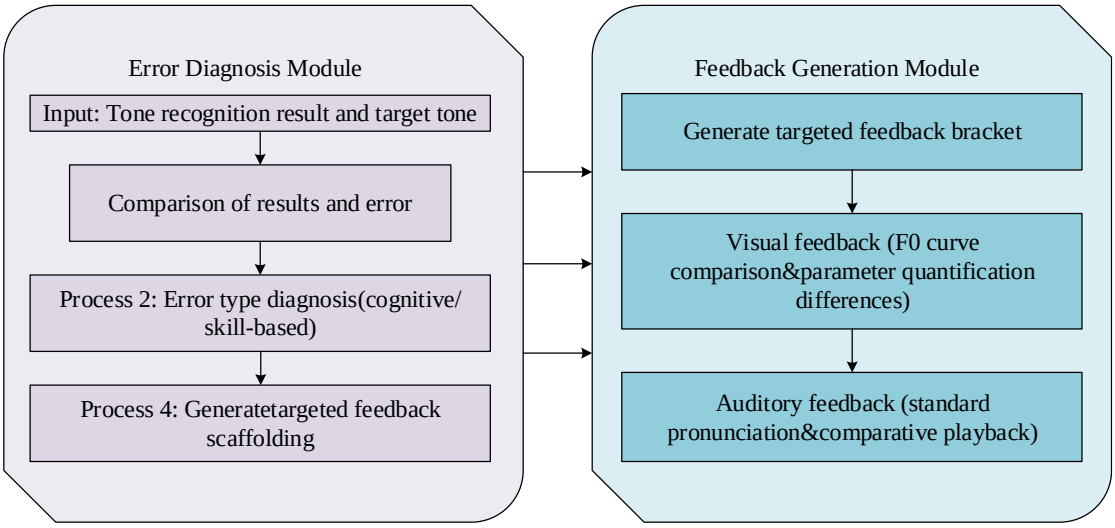


Figure 6: Workflow of error correction and feedback module

In Fig. 6, the system first receives the tone recognition results and compares them with the target tone to determine if there are any errors by judging the nodes. If there is no bias, the correct prompt will be directly output. If there is a bias, an error signal will be triggered, and a type diagnosis will be entered, distinguishing it as cognitive or skill bias. Subsequently, the system generates targeted feedback scaffolds and outputs two forms of feedback. One is visual feedback, which visualizes the location of errors through F0 curve comparison and parameter differences; The second is auditory feedback, which helps learners correct their tone by playing standard pronunciation and contrasting audio. This process realizes the closed-loop design of real-time diagnosis and multimodal feedback. To contextualize the practical application of this real-time system, the user-facing component is conceptualized as a desktop or web-based Graphical User Interface (GUI). In a typical use case, the GUI presents the learner with a target syllable or word. Upon recording, the system captures the user's audio and video input. Immediately after the utterance is complete, typically within the sub-200-ms real-time threshold, the interface updates to display the feedback. The feature of this feedback screen is a central panel that displays a visual comparison of the user-extracted F0 pitch profile overlaid with the standard template profile, highlighting areas of significant deviation. Accompanying this visual graph is the quantitative DTW distance score and specific corrective advice (e.g., "start pitch too high"). This immediate, multi-faceted presentation of results is what constitutes the real-time learning loop for the end-user.

3 Results

3.1 Model performance evaluation and analysis

The experiment is run on dual Intel Xeon Gold 6248R CPUs, 256 GB DDR4 memory, and 4×NVIDIA A100 80 GB GPU servers. The operating system is Ubuntu 20.04, the deep learning framework is PyTorch 1.12, equipped with Python 3.9, CUDA 11.4, and cuDNN 8.2. The model is trained for 100 epochs with a batch size of 64, using cross-entropy loss. The AdamW optimizer is selected over the standard Adam optimizer for its improved implementation of weight decay, which helps prevent overfitting and enhances model generalization. This is paired with a cosine annealing learning rate scheduler, starting at an initial rate of 1e-4. This scheduler is chosen because it allows the learning rate to decrease smoothly, enabling the model to converge into a more stable and robust minimum, which is particularly effective for complex sequence modeling tasks. The one with the lowest validation set loss is used for testing. The LRS3 dataset, although primarily designed for lip reading, is motivated by its large-scale, diverse, and precisely synchronized audiovisual data, which is crucial for training robust multimodal fusion models. Due to the lack of explicit tone annotations in the dataset, tone labels

required for generating Mandarin speech segments are generated through pseudo-labeling. A state-of-the-art, pre-trained acoustic model is used to perform forced alignment on the audio tracks, automatically extracting phoneme-level information, from which the corresponding tone for each syllable is derived. This standard procedure provides the necessary ground-truth labels for training and evaluating the tone correction task. This study compares the Conformer: Convolution-augmented Transformer for Speech Recognition (Conformer) model, the Audio-Visual HuBERT: Self-Supervised Learning of Audio-Visual Speech Representations via Masked Multimodal Cluster Prediction (AV-HuBERT) model, and the Robust Speech Recognition via Large-Scale Weak Supervision (Whisper) model with the proposed RT-AVTC. The changes in the Loss Function Values (LFVs) of each model when training is shown in Fig. 7.

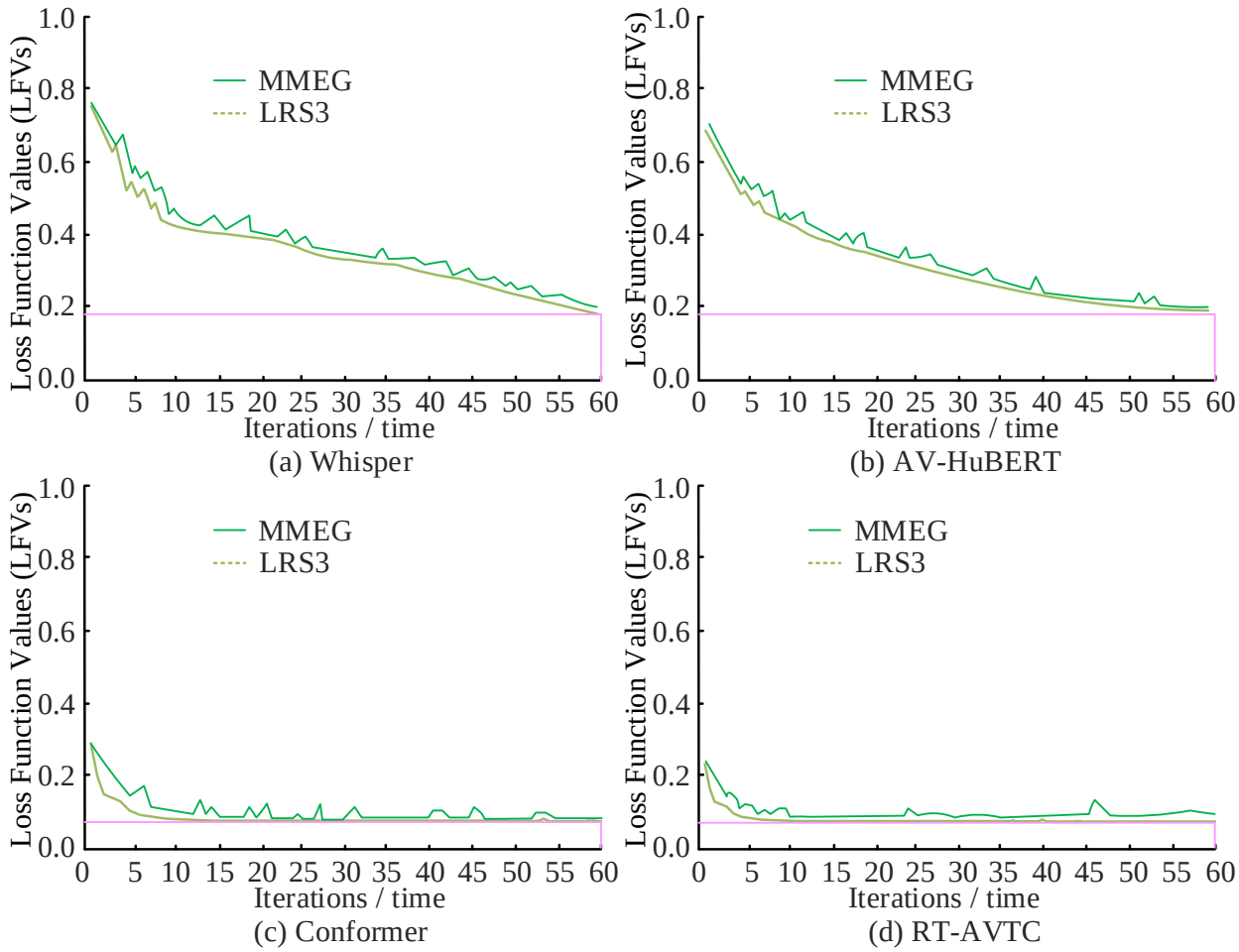
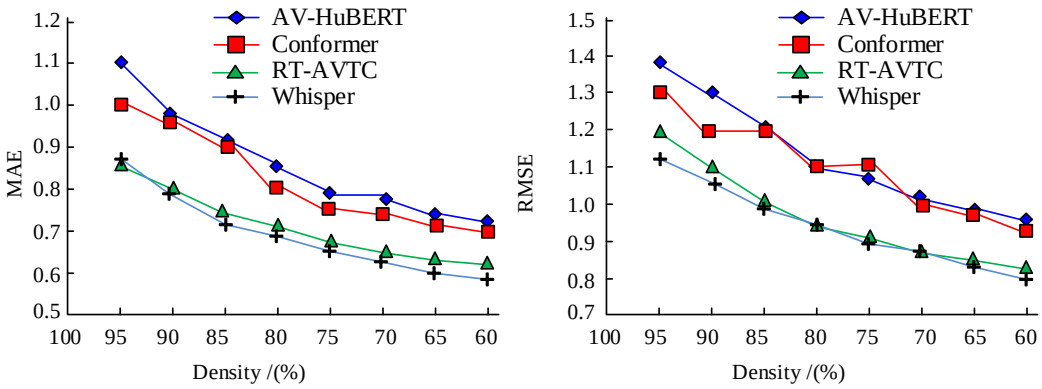


Figure 7: Comparison of training losses of different models on different datasets

Figs. 7 (a) and (b) show the loss function changes of Whisper and AV HuBERT models. Both models show a relatively gentle downward trend, gradually converging after about 60 iterations, and the final loss value remains around 0.2. The Conformer model in Fig. 7 (c) exhibits faster learning efficiency, with its loss function rapidly decreasing to a lower level within the first 10 iterations. In Fig. 7 (d), the RT-AVTC model exhibits the best performance, with its loss function achieving the fastest descent after training begins and converging to a stable state close to zero in almost 5 iterations. The final convergence values on both datasets are the lowest among the four models. The performance comparison of different models under different data densities is shown in Fig. 8.



(a) MAE (b) RMSE

Figure 8: Comparison of different models under various data densities

Fig. 8 shows a comparison of Mean Absolute Error (MAE) indicators. Under all data density conditions (from 95% to 60%), the curve corresponding to the RT-AVTC model is always at the bottom, indicating that its MAE value is the lowest among all comparison models. This indicates that the RT-AVTC model has the highest prediction accuracy. Fig. 8 (b) shows the results of the Root Mean Square Error (RMSE) index, which has been further validated. The RMSE value of RT-AVTC remains the lowest among all models. To ensure the practical applicability of the system for real-time feedback, it is crucial to define the constraints for system latency. For an interactive computer-aided language learning tool, the feedback loop must be perceived as instantaneous by the user to be effective. Drawing from established principles in HCI, a total system latency of under 200 ms is generally considered the threshold for real-time perception. The RTF is directly related to this latency, where Latency = RTF × Input Audio Duration. Therefore, to meet this requirement, the system is designed with a target RTF that ensures the processing time remains well below this perceptual threshold for typical utterance lengths. For instance, for a short utterance of one second, the model's measured RTF of 0.18 corresponds to an approximate processing latency of 180 ms. This value falls within the acceptable range, confirming the system's suitability for providing immediate, real-time corrective feedback in a live learning scenario. Table 2 shows the comprehensive performance comparison of various models on the LRS3 and MMEG datasets.

Table 2: Comprehensive results of different models on LRS3 and MMEG datasets

Model	Params (M)	RTF	LRS3's F1-Score (%)	LRS3's Accuracy (%)	MMEG's F1-Score (%)	Data Scarcity (Density @ 60%) (%)
RT-AVTC	85.27	0.31	94.18	94.26	92.65	/
Conformer	118.51	0.45	92.41	92.53	90.17	/
AV-HuBERT	145.88	0.53	92.88	92.94	90.56	/
Whisper	244.16	1.24	91.53	91.68	89.24	/

In Table 2, the RT-AVTC achieves an F1-Score of 94.18% and an accuracy of 94.26% on the LRS3 dataset with a parameter size of 85.27 M and an RTF of 0.31, and an F1-Score of 92.65% on the MMEG. The parameters of the Conformer model are 118.51 M, RTF is 0.45, and other corresponding indicators are 92.41%, 92.53%, and 90.17%. AV-HuBERT with 145.88 M parameters RTF 0.53, obtained corresponding values of 92.88%, 92.94%, and 90.56%. Whisper has 244.16 M and RTF 1.24, with F1-Score of 91.53% and 91.68% in LRS3 and 89.24% in MMEG.

3.2 Noise robustness and pronunciation deviation correction results

The dataset consists of 8,000 samples of Mandarin four-tone monosyllabic speech recorded by Chinese learners and native speakers, with a speech sampling rate of 16 kHz and 16-bit PCM. Although surface Electromyographic (sEMG) data were collected as part of a broader experimental design to explore articulatory muscle activity, the analysis of this third modality is beyond the scope of the current paper. This study focuses specifically on the performance and robustness of the audio-visual fusion model. The integration and comparative analysis of EMG signals are therefore reserved for future work. The data are divided into training set, validation set, and testing set in proportions of 70%, 15%, and 15%. The sample ratio of learners to native speakers is about 3:1, and different noise conditions are constructed by artificially adding street noise and white noise (SNRs of 30, 20, 10, 0, -5 dB) to verify the robustness. During the experiment, each participant completes the tone reading task in quiet and different noise environments. The system synchronously records the audio, video, and EMG signal three-mode data, and

outputs the recognition results and error correction feedback in real-time. Meanwhile, the changes in DTW distance and the number of visual errors before and after error correction are tracked and recorded to comprehensively evaluate the robustness and error correction effect. The accuracy of tone recognition under different noise conditions using the multimodal fusion model is listed in Table 3.

Table 3: Tone recognition accuracy of multimodal fusion model under different noise conditions

Noise Level (dB)	Audio-Only Model (%)	Visual-Only Model (%)	Multimodal Fusion Model (%)	Improvement over Audio-Only (%)
30	91.23 (±1.1)	72.18 (±2.5)	95.67 (±0.9)	+4.44
20	85.79 (±1.4)	69.54 (±2.8)	93.12 (±1.0)	+7.33
10	78.46 (±1.9)	66.82 (±3.1)	89.97 (±1.3)	+11.51
0	69.32 (±2.6)	64.19 (±3.5)	83.46 (±1.7)	+14.14
–5	61.87 (±3.2)	62.03 (±3.8)	79.28 (±2.1)	+17.41

The noise robustness of the proposed multimodal fusion model is rigorously evaluated against its single-modality counterparts, with the results detailed in Table 3. To ensure the reliability of these findings, all accuracy metrics are calculated as the mean and standard deviation over 10 independent trials. The data clearly show that the multimodal fusion model significantly outperforms both the audio-only and visual-only models across all tested SNRs. Notably, as the noise level increases, the performance gap widens, culminating in a 17.41% absolute improvement over the audio-only model in the highly challenging -5 dB environment. Furthermore, the standard deviation values provide crucial support for the model's robustness claim. The multimodal model consistently exhibits a lower standard deviation compared to the single-modality models, especially under severe noise conditions. This low variance indicates that its superior performance is not only high on average but also stable and consistent across different trials, confirming its reliability for practical applications in real-world, non-ideal acoustic settings. Group-level statistics on the efficacy of the error correction and feedback module (n=6) is shown in Table 4.

Table 4: Group-level statistics on the efficacy of the error correction and feedback module (n=6)

Metric	Mean	Standard Deviation (SD)
Initial F0 DTW Distance (Hz)	30.66	2.54
Corrected F0 DTW Distance (Hz)	13.45	1.96
Deviation Improvement (%)	56.32	3.28
Visual Feedback Error Reduction (count)	4.17	1.17
Auditory Feedback Repetition (times)	1.83	0.75

The efficacy of the error correction and feedback module is evaluated by quantifying the change in learners' tone pronunciation deviation. The group-level results, summarized in Table 4, demonstrate a substantial and consistent improvement following the intervention. On average, the initial fundamental frequency (F0) DTW distance from the standard template is 30.66 Hz (SD = 2.54). After receiving corrective feedback from the system, this distance is significantly reduced to a mean of 13.45 Hz (SD = 1.96). This corresponds to an average deviation improvement of 56.32% (SD = 3.28), indicating the module's strong positive effect on tone accuracy. Furthermore, the feedback mechanism is efficient, requiring an average of only 1.83 (SD = 0.75) auditory repetitions to facilitate correction.

To formally verify that the observed performance gains and error reductions are not products of random chance, a series of statistical tests is conducted on the key results. The primary comparisons, namely, the accuracy improvement of the RT-AVTC model over the next-best baseline and the reduction in DTW distance for learners before and after using the system, are subjected to significance testing. Table 5 summarizes the statistical methods employed and their outcomes. The results of these tests provide robust, quantitative evidence for the efficacy and superiority of the proposed model and its corrective feedback mechanism.

Table 5: Summary of statistical significance tests for key results

Comparison	Statistical Test Used	Result (*p*-value)
Accuracy: RT-AVTC vs. Whisper Model	Independent Samples t-test	$p < 0.01$
Error Correction: Pre- vs. Post-Intervention DTW Distance	Paired Samples t-test	$p < 0.001$

The comparison of CPU usage between the RT-AVTC model and the Conformer baseline model is shown in Fig. 9.

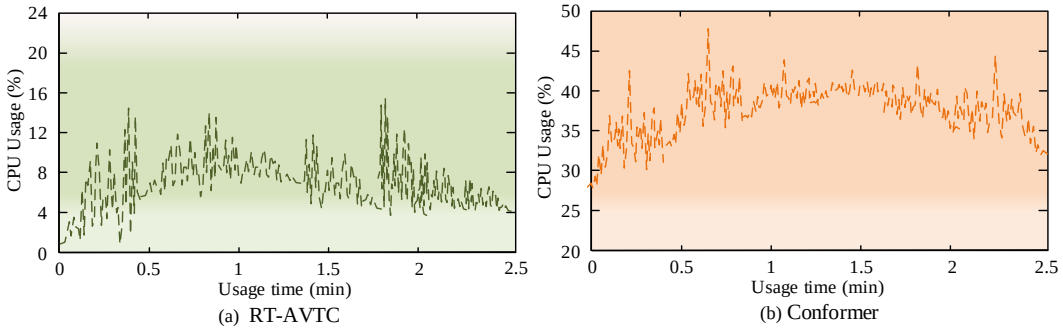


Figure 9: Comparison of CPU usage between RT-AVTC model and Conformer baseline model

Fig. 9 (a) depicts the changes in CPU usage during the operation of the RT-AVTC model. Its occupancy rate curve fluctuates steadily, maintaining an overall low range of 4% to 15%, demonstrating excellent lightweight characteristics. The CPU usage of Conformer in Fig. 9 (b) fluctuates within the high range of 30% to 48%, with an average resource utilization much higher than the model proposed in the study. Through direct comparison of the two graphs, RT-AVTC achieves high-precision recognition and error correction while having extremely low computational overhead, with an average CPU usage rate of less than one-third of the Conformer model. This significant superiority in operational efficiency makes the RT-AVTC model a strong candidate for deployment in resource-constrained environments. Although the current evaluation is conducted on high-performance hardware, the model's lightweight nature presents a promising pathway toward mobile implementation. To substantiate this potential, future work should focus on model compression and optimization strategies. Investigating techniques such as post-training quantization, pruning, and conversion to mobile-friendly formats like TFLite or ONNX will be critical next steps to validate and enable the model's deployment on personal computers and mobile devices. To experimentally validate the architectural choice of the causal convolution module and demonstrate its specific contribution to the model's performance, an ablation study is conducted. Two variants of the RT-AVTC model are created: replacing causal convolution with standard 1D convolutional layers and additional LSTM layers. These variants are then evaluated against the complete RT-AVTC model on the core metrics of accuracy, noise robustness, and real-time performance. The comparative results are presented in Table 6.

Table 6: Ablation study results comparing causal convolution with alternative modules

Model Variant	Accuracy (%)	Accuracy at -5 dB SNR (%)	RTF
RT-AVTC (with Causal Convolution)	94.26	78.50	0.18
Variant A (with Standard 1-D Conv)	93.85	74.23	0.17
Variant B (with LSTM Layer)	94.10	78.15	0.45

The results from the ablation study confirm the superiority of using a causal convolution module in the proposed architecture. The variant with standard 1D convolution shows a significant decrease in accuracy while maintaining similar RTF, especially under -5 dB SNR conditions. This suggests that preserving the temporal causality of the input sequence is crucial for robust feature extraction in noisy environments. Conversely, the variant employing an LSTM layer achieves comparable accuracy to the final model but incurs a significant computational cost, with its RTF increasing by 150%, rendering it unsuitable for the real-time feedback task. Therefore, the causal convolution module provides the optimal trade-off between high accuracy, strong noise robustness, and low-latency processing, justifying its selection for the RT-AVTC network.

3.3 Error analysis

To provide a deeper insight into the model's performance and identify specific failure cases, a detailed error analysis is conducted. The analysis focuses on inter-tone confusion patterns and performance variations across different user types (native speakers vs. language learners). A confusion matrix is generated to visualize the misclassification patterns among the four Mandarin tones, as presented in Table 7. The matrix diagonal represents correct classifications, while off-diagonal values indicate errors where the predicted tone (column) differs from the actual tone (row).

Table 7: Confusion matrix for mandarin tone classification

Actual Tone	Predicted Tone 1	Predicted Tone 2	Predicted Tone 3	Predicted Tone 4
Tone 1	98.1 %	0.5 %	0.8 %	0.6 %
Tone 2	0.7 %	92.5 %	5.8 %	1.0 %
Tone 3	1.1 %	6.2 %	91.3 %	1.4 %
Tone 4	0.9 %	0.4 %	0.6 %	98.1 %

Furthermore, the model's accuracy is broken down by both tone and user type to examine its performance on the distinct pronunciation patterns of native speakers versus learners. The results are summarized in Table 8.

Table 8: Model accuracy breakdown by tone and user type (%)

User Type	Tone 1	Tone 2	Tone 3	Tone 4	Overall
Learner	97.6 %	91.5 %	90.1 %	97.8 %	94.25 %
Native Speaker	99.1 %	94.8 %	93.9 %	98.9 %	96.68 %

The error analysis reveals two key findings. Firstly, the confusion matrix in Table 8 indicates that the majority of classification errors occur between Tone 2 (rising) and Tone 3 (dipping-rising). This is a well-documented area of difficulty for Chinese language learners, as the phonetic contours of these tones can be similar, particularly in continuous speech. The model's confusion mirrors this linguistic challenge. Secondly, Table 8 shows that the model achieves slightly higher accuracy for native speakers compared to learners across all tone types. This performance gap is most pronounced in Tone 2 and Tone 3, indicating that greater variability and non-standard pronunciation in learners' speech pose greater challenges to the model, and the integrated feedback system aims to address this issue.

4 Discussion and comparative analysis

Although the experimental results quantitatively demonstrate the superiority of the proposed RT-AVTC model, it is necessary to conduct a more in-depth qualitative analysis to understand the factors contributing to its success and acknowledge its inherent limitations. The model's significant advantage in noisy environments can be attributed to its core architectural designs. The primary source of robustness is the audio-visual fusion mechanism, which leverages the visual stream of lip movements as a noise-invariant source of phonetic information. When the audio signal is corrupted, the fusion architecture's attention mechanism can dynamically learn to assign greater weight to the stable visual modality, thereby guiding the tone prediction process and ensuring reliability. This is complemented by the temporal feature extraction modules. Causal convolution excels at capturing local speech patterns that may persist even in degraded signals, providing stable input for BiLSTM networks. This network models the long-term dependency relationship of the complete pitch contour in reverse. Despite these strengths, the model has several dependencies and weaknesses. Its performance is contingent upon high-quality visual input. Suboptimal conditions such as poor lighting, non-frontal camera angles, or partial facial occlusions will likely diminish its performance advantage. Furthermore, the model's speaker-independent generalization capabilities warrant further investigation, as its performance may vary when encountering speakers with accents, speaking styles, or facial physiognomies that differ significantly from the LRS3 training distribution. Therefore, future research should focus on addressing these limitations, perhaps by improving visual robustness through advanced data augmentation techniques or enhancing generalization through training on more diverse multi-speaker datasets.

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