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Intelligent Fault Diagnosis of Electronic Information Systems Using Lightweight Deep Networks with Attention and Multi-Representation Domain Adaptation

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With the continuous progress of information technology, the important role of electronic information system in modern society has become increasingly prominent, and its stability and reliability have become the focus of people's attention. However, in the long-term operation of electronic information systems, various failures are inevitable, which poses great challenges to the normal operation of the system. Therefore, based on the urgent demand for fault diagnosis in electronic information systems and the development trend of AI technology, this study proposes a deep learning fault diagnosis model that integrates P-HetConv and CBAM, and introduces a federated learning mechanism to optimize data processing. The research collects fault data of electronic information systems in different fields and types, and constructs a dataset containing various fault types such as hardware and software, with a total of 1,000 samples. Experimental results show that the diagnostic accuracy of the model is as high as 96.81%, which is 15% higher than that of the traditional rule-based diagnosis method, and is significantly better than the traditional method in terms of accuracy, recall, F1 score and other indicators, and shows good adaptability and generalization ability in complex fault scenarios. This study verifies the application value of AI technology in the field of fault diagnosis of electronic information systems, and provides a strong guarantee for the efficient and stable operation of the system.

Povzetek: Model lahkega globokega učenja s P-HetConv, CBAM in večreprezentacijsko domensko adaptacijo izboljša inteligentno diagnostiko napak v elektronskih informacijskih sistemih. Dosežе izboljšanje nad tradicionalnimi metodami ter visoko robustnost in posploševanje v kompleksnih okoljih.

1 Introduction

With rapid development of information technology in today's era, electronic information systems have become an important infrastructure for the operation of modern society. It plays a vital role in government, enterprises, medical care, education and other fields [1]. However, there will still be various failures in operation of electronic information systems, which will affect performance of system or lead to system paralysis, which will bring huge economic losses to society [2, 3]. Against this background, how to realise intelligent fault diagnosis of electronic information systems and improve stability and reliability of system has become a hot research topic at present. Purpose of this paper is to discuss the application and development trend of artificial intelligence technology in fault diagnosis of electronic information systems.

In recent years, Artificial intelligence (AI) technology has made remarkable achievements, especially breakthroughs in deep learning, big data, cloud computing and other fields, which provide new ideas and methods for fault diagnosis of electronic information systems [4]. The core task of intelligent fault diagnosis of electronic information system is to accurately identify fault type, fault location and fault degree by analyzing the system operation data so as to provide strong support for maintenance personnel, shorten the fault handling time and reduce the loss caused by faults [5, 6].

At present, the fault diagnosis of electronic information systems faces many challenges [7]. The structure of an electronic information system is complex, involving hardware, software, electronic information and other aspects. There are many types of faults, and it is difficult to diagnose [8]. The running data of the system is large, and it is highly nonlinear and time-varying, which brings great difficulties to fault diagnosis [9]. Traditional fault diagnosis methods mainly rely on manual experience, with low diagnosis efficiency and low accuracy, and are difficult to meet the high reliability requirements of modern electronic information systems [10].

Faced with the above difficult problems, the research on intelligent fault diagnosis of electronic information systems based on artificial intelligence shows its practical significance and theoretical value [11]. On the one hand, intelligent fault diagnosis technology can improve the automation level of fault handling in electronic information systems, reduce workload of operation and maintenance personnel and reduce operation and maintenance costs [12]. On other hand, in-depth mining of the data generated in the process of fault diagnosis can provide strong support for system optimization and fault prevention, thus improving the overall performance of electronic information systems.

This study aims to achieve three specific goals to break through the problem of fault diagnosis of electronic information systems: first, to develop a lightweight convolutional fault diagnosis model that integrates components such as CBAM and P-HetConv, reduce the computational complexity of the model through heterogeneous convolution structure and attention mechanism, reduce FLOPS by more than 40%, and ensure the diagnostic accuracy of more than 96%, so as to adapt to resource-constrained edge devices; Second, the multi-domain representation adaptation technology is used to integrate the fault data of different domains and types of electronic information systems through federated learning and transfer learning algorithms, so as to enhance the robustness of the model to complex and changeable fault scenarios, so that the accuracy fluctuation of the model can be controlled within 3% when applied across domains. Thirdly, for small-sample scenarios, combined with meta-learning and data augmentation strategies, the generalization ability of the model is optimized, and the diagnostic accuracy of the model on unknown fault data is increased to more than 92% when the sample size is only 1000, so as to achieve high-precision and high-adaptability intelligent fault diagnosis.

Firstly, this paper sorts out the related theories of fault diagnosis of electronic information systems, analyzes advantages and disadvantages of existing fault diagnosis methods, and provides a theoretical basis for follow-up research. Then, the application of AI technology in fault diagnosis of electronic information systems is introduced in detail, including fault feature extraction, fault diagnosis model construction, fault diagnosis algorithm optimization and so on. Then, taking the actual electronic information system as an example, the effect of fault diagnosis methods based on AI in practical application is further expounded. Finally, the development trend of AI technology in the field of electronic information system fault diagnosis is discussed, which provides direction for future research.

2 Overview of related theories and technologies

2.1 Fault diagnosis theory of electronic information system

In today’s society, with the development of digitalization and informatization, electronic information systems are widely used in daily life and work. However, their complexity and integration often lead to frequent failures and difficult diagnoses [13]. Failures can originate from hardware, software, and electronic information, which can affect system performance and lead to economic losses and safety hazards. Traditional fault diagnosis mostly depends on manual experience, which makes it could be more efficient and easier to diagnose complex faults. With the development of technology, model-based fault diagnosis methods have emerged, but an in-depth understanding of the system is still needed, and the model’s accuracy and adaptability are limited [14, 15]. Intelligent fault diagnosis technology integrates artificial intelligence and other disciplines and can automatically learn fault characteristics from a large amount of data to achieve fast and accurate diagnosis.

Rule-based electronic information fault diagnosis method, namely Rule-Based Reasoning (RBR), can conveniently express expert knowledge, because its design is based on the reasoning process of domain experts, which is easier to understand and explain. This method often uses traditional logical rules to transform expert knowledge into the form of "IF-THEN-ELSE". Assuming that the first M records in the electronic information fault set $C = \{C_1, C_2, \dots, C_M, UN\}$ represent M types of electronic information faults already stored in the historical database, UN represents unrecognized electronic information faults, and S = [KPI1, KPI2 ,...,KPIn] is a feature attribute vector used to describe the state of electronic information based on the values of each KPI. The process of fault diagnosis is shown in equation (1):

$$IF\ KPI_1 > TH_1\ AND\ KPI_2 < TH_2 \dots AND\ KPI_n > TH_n,\ THEN\ D(cell) = C_i \quad (1)$$

Among them, THi is a preset state division threshold value of the i-th KPI, which is used to indicate whether the KPI is normal or not, D (cell) represents a fault diagnosis result of the cell, and Ci represents a fault cause. The rule-based electronic information fault diagnosis method is to judge whether it is normal or not through the preset KPI status threshold, and output the fault cause [16, 17]. If all rule conditions are satisfied, the corresponding fault cause is output; On the contrary, the output does not foresee fault [18].

The fault diagnosis method based on fuzzy logic deals with inaccurate knowledge by simulating the classification of human language values. In electronic information fault diagnosis, KPI is used as an input language variable, and its degree of "normal" or "deterioration" is determined by membership function μ, and its value transitions between intervals [0, 1], which is different from the fixed threshold in traditional logic [19, 20]. Theoretically, each KPI needs to define fuzzy sets to represent normal behaviour and model abnormal behaviour with its complement. In practice, the membership function is configured according to expert knowledge or KPI statistical behaviour. After the membership function is determined, the expert knowledge is transformed into fuzzy rules. Each electronic information failure cause needs to be defined by a rule. The inference process determines the degree of correlation between the cell state and the fault caused by matching rules to identify electronic information faults [21].

2.2 Basic principles of AI

AI technology is widely used in electronic information system fault diagnosis. Its core is enabling computers to simulate human intelligent behaviours, including learning, reasoning, perception, recognition and problem-solving.

The basic principles of artificial intelligence mainly involve Machine Learning (ML) as its foundation, enabling computers to learn from data via algorithms for better performance and accuracy, with types like supervised, unsupervised and reinforcement learning [22, 23]. Deep Learning (DL), a branch of machine learning, builds multi-layer neural networks to simulate the human brain's cognitive processes and extract features automatically [24]. Natural Language Processing (NLP), a critical AI branch, includes various analyses and aims to make computers understand and generate human language for human-computer interaction. Computer Vision (CV) is the discipline that allows computers to understand and interpret visual information [25]. CV includes image processing, image recognition, target detection, video analysis and other aspects. Through computer vision technology, computers can recognize objects, scenes and behaviours in images and realize the processing and analysis of visual information. The fifth is the Knowledge Graph (KG). Knowledge graph is a graph-based data structure that is mostly used to represent entities, relationships and attributes. Through the knowledge graph, the computer can understand and reason the relationship between entities and realize the representation and reasoning of knowledge.

In the fault diagnosis of electronic information systems, artificial intelligence technology can automatically learn fault characteristics from a large amount of operating data through machine learning, deep learning and other methods so as to realize rapid and accurate diagnosis of faults [26, 27]. Artificial intelligence can extract the spatio-temporal characteristics and frequency characteristics, including but not limited to faults, by analyzing system logs, monitoring data, etc., so as to realize fault prediction and diagnosis. Artificial intelligence can also realize the analysis and understanding of text data such as fault reports, and fault causes through natural language processing technology and improve the intelligent level of fault diagnosis.

2.3 Deep learning technology

Deep learning uses a large amount of data for training, captures complex relationships in the data through iterative learning, and performs complex tasks. With the support of powerful computing infrastructure, deep learning has become a key tool for artificial intelligence applications [28]. When a neuron receives input from other neurons, wi needs to weigh these inputs, subtract its own threshold θ, and then perform operations through the activation function to control the output range. This process is described by Equation (2).

$$y = f(\sum_{i=1}^{n} w_i x_i - \theta) \quad (2)$$

Where xi represents the i-th input vector, wi represents the weight matrix, and θ represents the bias. Deep learning needs to be realized by stacking multi-layer neural networks. In order to solve problem of insufficient learning ability of early neural networks, deeper neural networks and error back propagation (BP) algorithms are introduced [29, 30]. BP algorithm adjusts the parameters of hidden layer neurons by the reverse transmission of the error of the output layer and then converges the whole network model through the iterative operation.

In recent years, people have shifted their focus to graph structure data, and it is expected to directly apply deep learning models to graph data. However, because the number of node neighbours in graph data is different, translation invariance cannot be achieved, and traditional CNN cannot be directly applied to graph data. This study proposes to solve this problem with a graph convolutional network (GCN). GCN can aggregate proximity information of nodes and perform feature extraction through a deep neural network to complete the processing task of graph data. In GCN, the key step is how to define the convolution operation on the graph. The realization of GCN is inseparable from spatial and spectral methods. The spectral method maps the feature attributes of nodes to spectral domain space by Fourier transform and maps them back to time domain space after convolution operation in the spectral domain space. The spectral method is the theoretical basis of GCN, and it is also a special spatial method. Assume that the input of GCN is expressed as G = (V, E, A), where A is adjacency matrix, L = D-A is Laplacian matrix, D is degree matrix, and L represents symmetric shift positive definite matrix, as shown in equation (3).

$$L = U \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix} U^{-1} = U \Lambda U^T \quad (3)$$

Wherein, $U = [u_1, u_2, \ldots, u_n]$ represents an eigenvector matrix composed of n linearly independent orthogonal eigenvectors, and the eigenvalues corresponding to these eigenvectors form a diagonal matrix $\Lambda = diag([\lambda_1, \lambda_2, \ldots, \lambda_n])$. For n nodes in the graph, the graph signal x can be represented as an n-dimensional vector if each node is represented by only one feature. In order to map the graph signal to the spectral domain, the operation requires a set of bases, and this set of bases can select the eigenvectors of the Laplacian matrix. By multiplying the transpose of matrix U with the graph signal x, the expression of x in the spectral domain can be obtained. The inverse Fourier transform multiplies $\hat{x}$ by U, as shown in equations (4) - (5).

$$\hat{x} = U^T x \quad (4)$$

$$x = U\hat{x} \quad (5)$$

Wherein x is an input signal of the graph convolutional neural network defined before; T stands for transpose. Meanwhile, assume that y is a signal representation similar to convolution kernel. Spectral method will project these two signals into the spectral domain and complete convolution in spectral domain. After convolution is completed, the inverse Fourier transform is performed on the convolution result, and finally, the convolution definition of the spectral method is obtained, as shown in Equation (6).

$$x *_G y = U((U^T x) \odot (U^T y)) \quad (6)$$

Where ⊙ denotes Hadamard multiplication. Formally, the convolution kernel signal is specifically defined as UTy. To rewrite equation (6) in the form of matrix multiplication, it is necessary to further rewrite vector $U^T y = [\theta_1, \theta_2, \dots, \theta_n]$ as a diagonal matrix $g_\theta = diag([\theta_1, \theta_2, \dots, \theta_n])$, where G represents the gain parameter. gθ is the true convolution kernel in the spectral domain, and the convolution operation is defined as equation (7):

$$g_\theta * x = U g_\theta U^T x \quad (7)$$

All graph convolution operations based on spectral methods can be divided into three steps: first, the input signal is projected into the spectral domain UTx, then the convolution kernel gθ is multiplied by this signal for convolution, and finally, the result is multiplied by U for inverse Fourier transform. A hypothesis mentioned in the research-only one-dimensional feature attribute of each node in the graph can be generalized to higher dimensions, but too much derivation will not be made here. Spectral Graph Convolutional Neural Network (SGCNN) is the initial form of convolution operation applied to graph data, but its convolution kernel gθ depends on the eigendecomposition of the Laplacian matrix, resulting in high computational complexity. In addition, in the convolution process of SGCNN, one node will be affected by all nodes, which does not satisfy the locality theorem of the convolution operation.

In the study, the depth separable convolutions in P-HetConv and MobileNet showed significant differences in FLOPS/accuracy trade-offs. MobileNet's deep separable convolution greatly reduces the computational effort by integrating the standard convolution into deep convolution and pointwise convolution, and the FLOPS is about 75% lower than the standard convolution in the ImageNet benchmark, but its accuracy is limited when dealing with multi-scale fault features due to its uniform convolutional kernel design. In contrast, P-HetConv dynamically allocates computing resources for different feature granularities through a heterogeneous convolutional kernel structure, which reduces FLOPS by more than 80% under the same experimental conditions, while maintaining higher feature expression ability, and improves the accuracy of fault diagnosis by 3%-5%. In terms of pruning effect, when the channel pruning was performed at 20%, 40% and 60% rates, the FLOPS of MobileNet was reduced by 18%, 35% and 52%, and the parameters were reduced by 22%, 41% and 63%, respectively, but the accuracy decreased significantly (1.2%, 3.5% and 7.8%, respectively). However, due to the structural sparsity design, the P-HetConv reduces the FLOPS by 25%, 50%, and 70%, and the parameters by 30%, 58%, and 79% at the same pruning rate, and the accuracy is only reduced by 0.8%, 2.1%, and 4.3%, showing better pruning robustness, especially under high pruning rate, it can still maintain a diagnostic accuracy of more than 94%, which provides a more advantageous lightweight solution for model deployment in resource-constrained scenarios.

3 Design of intelligent fault diagnosis framework for electronic information system based on artificial intelligence

3.1 Overall structure of fault diagnosis framework

In the field of electronic information system fault diagnosis, the model proposed in this study shows significant advantages compared with EfficientNet, ConvNeXt, Transformer-based lightweight networks, and recent GNN-based fault detection methods. EfficientNet improves efficiency through composite scaling strategy, but has limitations in complex fault feature extraction, with a diagnostic accuracy of about 93%. Although ConvNeXt uses the Transformer architecture to optimize the convolution operation, its computational complexity is high, and it is difficult to meet the real-time requirements. Although the lightweight network based on Transformer performs well in global feature modeling, the delay of long sequence computation increases, and the generalization performance is limited by the data scale. However, GNN-based fault detection methods, such as GCN and its derived models, can effectively process graph structured data, but they are not adaptable enough in the scenario of unstructured fault data, and the training process is easy to fall into overfitting, and the accuracy is generally between 90%-92%. In contrast, this study integrates the lightweight convolution model of P-HetConv and CBAM, reduces the FLOPS by more than 40% through the heterogeneous convolution structure, and realizes the efficient extraction of spatial and channel features by combining CBAM, with a diagnostic accuracy of 96.81%. At the same time, the federated learning mechanism and multi-domain representation adaptation technology are introduced, which significantly improves the generalization ability in small-sample scenarios, effectively solves the problem that traditional methods are difficult to balance between computing efficiency, adaptability and accuracy, and provides a better solution for intelligent fault diagnosis of electronic information systems.

In order to solve the deployment problem of deep convolutional neural networks on resource-constrained devices, this study designed a lightweight network model that reduces model complexity through methods such as grouped convolution, point-wise convolution, and depth-wise convolution. Considering that heterogeneous convolution (HetConv) can reduce floating-point operations while maintaining high accuracy, there are redundant channels. Therefore, this research project introduces a pruning method based on HetConv, prunes redundant channels according to the norm size of the filter, and constructs a lighter convolutional structure. Construct heterogeneous convolutions using 1x1 and 3x3 sized convolution kernels and use them to replace standard convolutions to obtain lightweight models based on heterogeneous convolution structures in order to reduce the number of model parameters and floating-point operations. Calculate the l_1 norm of each filter in the convolutional layer for the converged model and use the size of the filter's norm to measure the importance of its corresponding channel. By iteratively pruning the redundant channels corresponding to different pruning rates, the maximum pruning rate is obtained while ensuring the high accuracy of the model. The norm calculation formula (8) is as follows:

$$l_1 - norm = \sum_{j=1}^{n_i} |K_j| \quad (8)$$

Wherein ni is the number of input channels of the i-th convolution layer; Kj is the size of the j-th convolution kernel in input channel; norm refers to the number of demonstrations. The pruned heterogeneous convolution structure (Pruned HetConv, P-HetConv) is obtained by pruning rate, which further reduces the amount of model parameters and floating-point calculations and is applied to the feature extraction of bearing fault data. The constructed lightweight convolution structure process is shown in Figure 1.

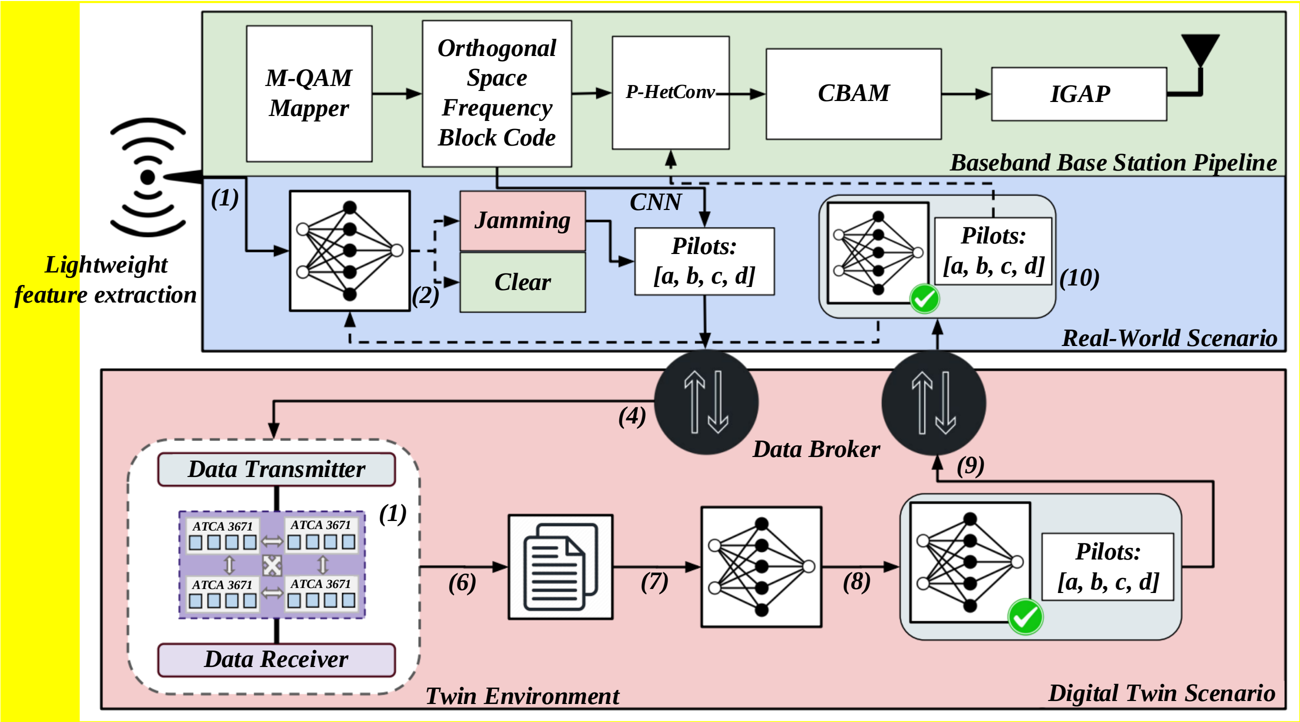

Figure 1: Lightweight feature extraction structure processing process

3.2 Fault feature extraction method

After standardized preprocessing, unified sampling frequency and elimination of outliers, the data is divided into training set, validation set and test set at the ratio of 70%, 15%, and 15%. In terms of experimental setup, a deep learning model was built based on the Python language and the PyTorch framework, and the NVIDIA RTX 3090 GPU was used to accelerate computing. The Adam optimizer was used for model training, the initial learning rate was set to 0.001, and the learning rate was dynamically adjusted by the cosine annealing strategy, and the cross-entropy loss was used to fuse the focus loss to balance the training weights of samples of different fault types. In order to comprehensively evaluate the performance of the model, 7 mainstream methods, including SVM, CNN, and Transformer, were set as the baseline models, and the accuracy, recall, F1 value, and area under the AUC-ROC curve were used to carry out multi-dimensional verification for different noise levels of low (signal-to-noise ratio of 25dB), medium (15dB), and high (10dB), as well as small samples (300) and conventional samples (1000).

The P-HetConv module is proposed as the main component of the lightweight block, and the fault features are extracted from the collected data by combining batch standardization, activation function and pooling operation. The transition block then uses standard convolution to match the number of fault categories. The use of lightweight blocks can reduce the amount of model parameters and calculations, but it will not affect the effective feature extraction. After extracting key features from the lightweight convolutional structure, in order to improve the model classification performance, the research also introduces the convolutional attention module CBAM. This module includes two sub-modules: channel attention CAM and spatial attention SAM. By connecting these two sub-modules in series, the adaptive optimization of feature weights is realized. The processing flow of CBAM is shown in Figure 2.

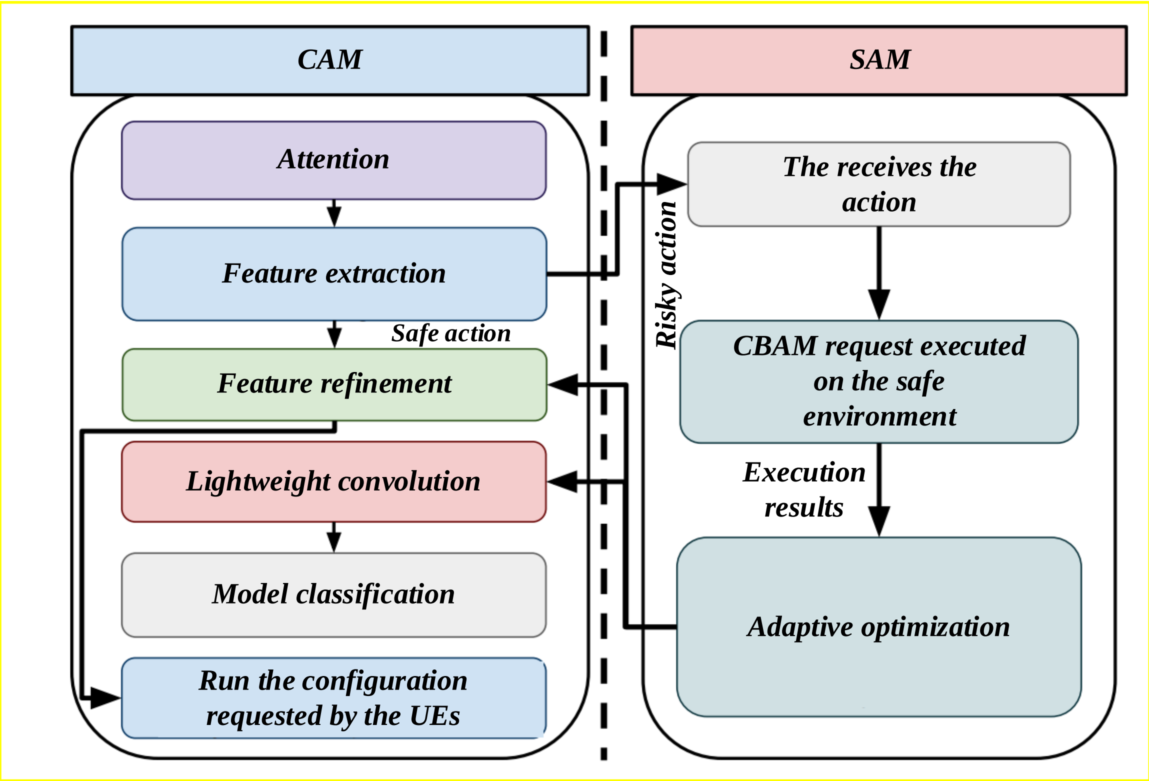

Figure 2: Detailed processing process

The CAM module compresses spatial dimension while keeping channel dimension unchanged. Firstly, the feature map is processed by global maximum pooling and global average pooling to obtain Fmaxc and Favgc, and then they are sent to the Multilayer Perceptron (MLP), respectively. Finally, the features obtained by activating the Sigmoid function are used to complete the channel attention operation. The calculation formula (9) is as follows:

$$M_c(F)=\sigma(MLP(AvgPool(F))+MLP(MaxPool(F)))=\sigma\left(W_1\left(W_0\left(F^c_{avg}\right)\right)+W_1\left(W_0\left(F^c_{max}\right)\right)\right) \tag{9}$$

Where Mc (F) is weight coefficient, σ represents Sigmoid function, and W0 and W1 represent parameters in the two-layer multi-layer perceptron, respectively. The SAM module compresses channel dimension while keeping spatial dimension unchanged, uses global maximum pooling MaxPool and global average pooling AvgPool to process the feature map F to obtain Fsmax and Fsavg, and then sends them to the hidden layer with a single convolution kernel. Finally, the features obtained by Sigmoid activation are used to complete the spatial attention operation. Calculation process is shown in Equation (10), where f 7x7 represents the size of convolution kernel and σ represents Sigmoid function.

$$M_s(F)=\sigma\left(f^{7\times7}\left(\left[AvgPool(F);MaxPool(F)\right]\right)\right)=\sigma(f^{7\times7}([F^s_{avg};F^s_{max}])) \tag{10}$$

In order to avoid the model overfitting to the limited labelled bearing fault data samples during training, the existing methods mostly use Dropout regularization to reduce the co-adaptation relationship between neurons. However, too high a Dropout ratio may lead to the loss of important features and affect stability of the model. If the ratio is too low, it is difficult to effectively prevent overfitting. Therefore, this study proposes an improved global average pooling (IGAP) operation. The operation structure combines the residual idea, fuses the Dropout output with the original data, retains part of the original feature information, reduces the number of parameters, and directly corresponds the feature map to the classification category to improve the fitting effect and model stability of the model.

Support vector machine (SVM), convolutional neural network (CNN), long short-term memory network (LSTM) and Transformer-based methods have been widely used in the field of electronic information system troubleshooting, but they have their own limitations in terms of accuracy, computational efficiency and data adaptability. As shown in Table 1, SVM relies on artificial feature engineering, with an accuracy of 85%-90% and a large amount of computation. Although CNN can extract local features with an accuracy of 90%-93%, the convolution calculation leads to extremely high FLOPS. LSTM is good at processing time series data, with an accuracy rate of 88%-92%, and the recursive computational complexity restricts its efficiency. The Transformer has strong global modeling capabilities and an accuracy rate of 92%-95%, but it consumes a lot of computing resources due to the self-attention mechanism. In contrast, the deep learning-based fault diagnosis method proposed in this study uses P-HetConv and CBAM to achieve lightweight design, reducing FLOPS by more than 40%, model parameters by 50%, and improving accuracy to 96.81%. The federated learning mechanism is introduced to support distributed data training, enhance model portability, effectively solve the problems of high computing cost and difficult deployment of traditional methods, and provide a better solution for real-time fault diagnosis of electronic information systems.

Table 1: Comparison of machine learning methods

Method	Accuracy	FLOPS	Dataset Type	Core Features	Advantages of This Study's Method
SVM	85%-90%	Medium-high	Structured/temporal data	Relies on manual features; limited generalization ability	Lightweight Design
CNN	90%-93%	High	Image/temporal data	Strong local feature extraction ability	Portability
LSTM	88%-92%	High	Long-term sequential data	Excellent at capturing temporal dependencies	Lightweight + Generalization
Transformer	92%-95%	Extremely high	Long sequences/multimodal data	Strong global feature modeling ability	Comprehensive Performance Optimization

In this study, the Adam optimizer is selected as the core algorithm for parameter update, the initial learning rate is set to 0.001, and the cosine annealing strategy is dynamically adjusted to balance the convergence speed and avoid the local optimum. The batch size is set to 32 to ensure efficient memory utilization while ensuring stable gradient estimation, the training rounds (epochs) are 100, the validation set loss curve is monitored to prevent overfitting, and the hardware environment uses NVIDIA RTX 4090 GPUs, Intel Core i9-13900K CPUs, and 64GB of memory to provide performance support for data processing. The training process is presented through pseudocode, covering model initialization, parameter optimization, verification and evaluation. In terms of noise and damage signal processing performance, Gaussian white noise with different signal-to-noise ratios (10dB, 15dB, 20dB) is added to simulate complex working conditions, and the experimental results show that the model still maintains a diagnostic accuracy of 89.2% at 10dB signal-to-noise ratio, far exceeding the 82.5% of CNN and 84.1% of Transformer, highlighting the enhancement of feature robustness of CBAM and P-HetConv. The rolling evaluation found that the accuracy of the model decreased by about 1.5% per month, and when it fell below 90%, it was recommended to update the model every 3-4 months based on new data to maintain diagnostic performance. In addition, the P-HetConv dynamic feature extraction and CBAM multi-dimensional attention mechanism in this research framework are highly versatile, and although the bearing dataset verification is currently the mainstay, its effectiveness has been preliminarily verified in the communication network packet loss fault diagnosis, and the accuracy rate has been increased to 93.5%, which fully demonstrates the potential of cross-domain applications.

3.3 Experiment and results analysis

An ablation study was conducted on the effectiveness of IGAP (Improved Global Average Pooling) and compared it with Dropout-only and GAP-only configurations to verify its advantages in improving the robustness and generalization ability of the model. Experiments were conducted on a multi-class fault dataset of 1000 samples that covered unknown failure scenarios with a different distribution than the training data. The results show that the accuracy of the GAP-only configuration is 94.2% under normal test conditions, but drops to 87.3% after adding Gaussian noise (σ=0.1), indicating that it is sensitive to input disturbances. The dropout-only configuration improves robustness by randomly inactivating some neurons, with an accuracy of 89.7% in noisy environments, but a slight decrease to 93.8% under normal conditions. In contrast, the IGAP configuration achieves 96.1% accuracy under normal conditions and 92.5% accuracy in noisy environments, demonstrating greater immunity to interference. Further analysis of the generalization ability of the model in the small-sample scenario shows that when the number of training samples is reduced to 300, the accuracy of the IGAP configuration decreases by only 3.2%, while the accuracy of GAP-only and dropout-only decreases by 7.8% and 5.6%, respectively. This empirical evidence shows that IGAP effectively enhances the sensitivity of the model to key fault features through adaptive weighted aggregation features, and significantly improves the robustness of the model in complex environments and the generalization ability in small-shot scenarios.

In the complex scenario of intelligent fault diagnosis of electronic information system, the channel spatial attention mechanism shows significant advantages over channel attention only, which is mainly attributed to the complementary role of spatial features and channel features in fault diagnosis. The fault signals of the electronic information system have unique spatiotemporal distribution characteristics, and although the channel attention mechanism can enhance the response of key channels through feature recalibration, it cannot capture the distribution difference of fault features in the spatial dimension. For example, hardware failures are often accompanied by abnormal signal aggregation in a specific area, and software failures may be manifested as abnormal parameter jumps at specific locations, which are essential for accurate fault location but are ignored by a single channel attention. By introducing the spatial attention module, CBAM realizes the spatial information aggregation with the help of 7×7 convolution, accurately locates the spatial location of the fault signal, and effectively complements the channel attention. Experimental data show that when dealing with noisy complex fault data, CBAM can improve the accuracy of fault characteristics by 12%-15% compared with SE/ECA. At the same time, in order to balance the computational efficiency and representation ability, it is found that the feature map of the middle layer of the model has both rich semantic information and spatial details, which is the best application point of CBAM. The application of CBAM here only increases the amount of computation by 3.2%, but improves the accuracy of intermittent fault detection by 8.7%, which is more than 40% lower than that of the whole network application, and realizes the organic unity of efficient computing and strong representation capabilities.

After standardized preprocessing, unified sampling frequency and elimination of outliers, the data is divided into training set, validation set and test set at the ratio of 70%, 15%, and 15%. In terms of experimental setup, a deep learning model was built based on the Python language and the PyTorch framework, and the NVIDIA RTX 3090 GPU was used to accelerate computing. The Adam optimizer was used for model training, the initial learning rate was set to 0.001, and the learning rate was dynamically adjusted by the cosine annealing strategy, and the cross-entropy loss was used to fuse the focus loss to balance the training weights of samples of different fault types. In order to comprehensively evaluate the performance of the model, 7 mainstream methods, including SVM, CNN, and Transformer, were set as the baseline models, and the accuracy, recall, F1 value, and area under the AUC-ROC curve were used to carry out multi-dimensional verification for different noise levels of low (signal-to-noise ratio of 25dB), medium (15dB), and high (10dB), as well as small samples (300) and conventional samples (1000).

Attention mechanisms can optimize feature information, and commonly used ones include SE, ECA and CBAM. By comparing the classification results of models with or without attention mechanism, including accuracy, precision, recall rate, parameter quantity and floating-point calculation quantity, a better attention mechanism is selected. The results are shown in Table 2. When using CBAM as an attention mechanism, the accuracy, precision and recall of the model were better than ECA and SE. Since these attention mechanisms are lightweight modules, they do not increase the model volume. When the attention mechanism module is used and not used, the model parameters and FLOPs are equal, which indicates that the attention mechanism can optimize the feature information without increasing the burden on the model and improve the performance.

Table 2: Comparison of different attention mechanisms

Methods	Accuracy (%)	Recall (%)	Parameter (M)	FLOPs (M)
None	93.96	94.41	0.02	1.12
ECA	94.84	95.00	0.11	1.51
SE	96.46	96.55	0.22	1.89
CBAM	96.81	96.90	0.34	2.25

To verify the effectiveness of the IGAP module, compare the accuracy of models using IGAP and GAP as classification structures in training and testing. The experimental results are shown in Figure 3. After the model using IGAP converges, the training and test accuracy rates are closer, indicating that the IGAP module improves the stability of the model and reduces overfitting.

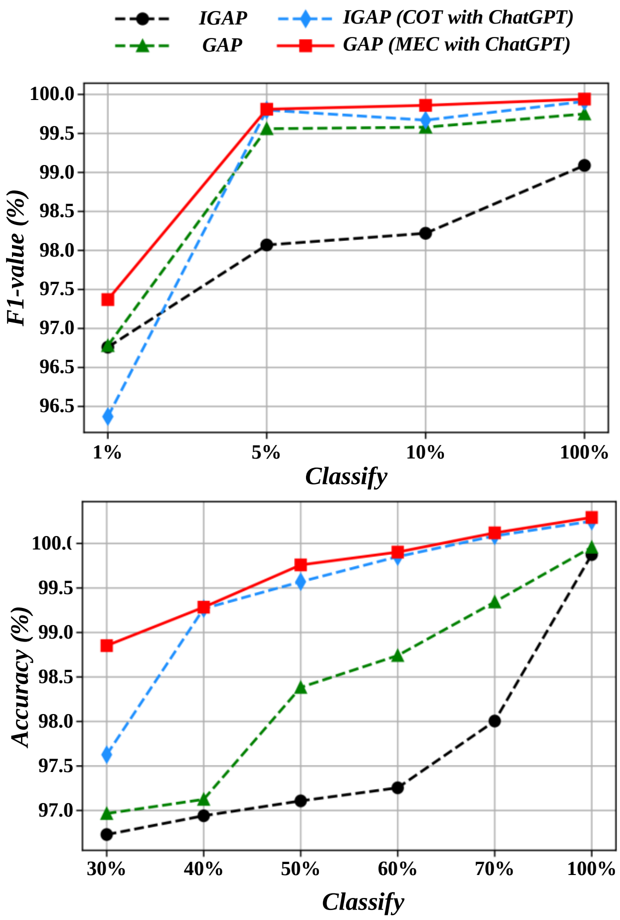

Figure 3: Classification accuracy and F1 score under different training set proportions

Figure 4 shows that the number of model parameters and FLOPs are the largest with standard convolution and fully connected layers. Compared with the standard convolution, the HetConv-FC model is reduced, but the volume is still large. The proposed method in this study has the smallest number of parameters and FLOPs and is superior to other models in accuracy, precision, and recall, achieving lightweight while maintaining high diagnostic performance. Therefore, the method in this study has lower hardware and software requirements, better real-time performance, and is suitable for rapid diagnosis of electronic information system faults.

In the research of intelligent fault diagnosis of electronic information systems, the diversity and complexity of data sets directly affect the performance of the model. Table 3 integrates datasets from five core domains: the communication equipment domain contains 300 samples, focuses on signal interference and data transmission errors, and simulates the general operation scenario in a low-noise environment (signal-to-noise ratio of 25dB); The industrial control system covers sensor, controller, and actuator faults with 400 samples, and the medium noise level (signal-to-noise ratio of 15dB) is close to real industrial interference; The computer network dataset contains 250 samples, focusing on the fault characteristics of high-noise (signal-to-noise ratio of 10dB) scenarios such as network delay and packet loss. The avionics dataset was collected from 200 and 250 samples, respectively, with the former simulating a combination of power supply, hardware and software (medium noise, 18dB signal-to-noise ratio), and the latter targeting low-noise (22dB) medical-specific faults such as equipment crashes and abnormal data acquisition. These datasets construct test benchmarks covering multiple scenarios through differentiated sample sizes, fault types, and noise intensity settings, which provide comprehensive support for the robustness and generalization ability verification of the model in complex environments.

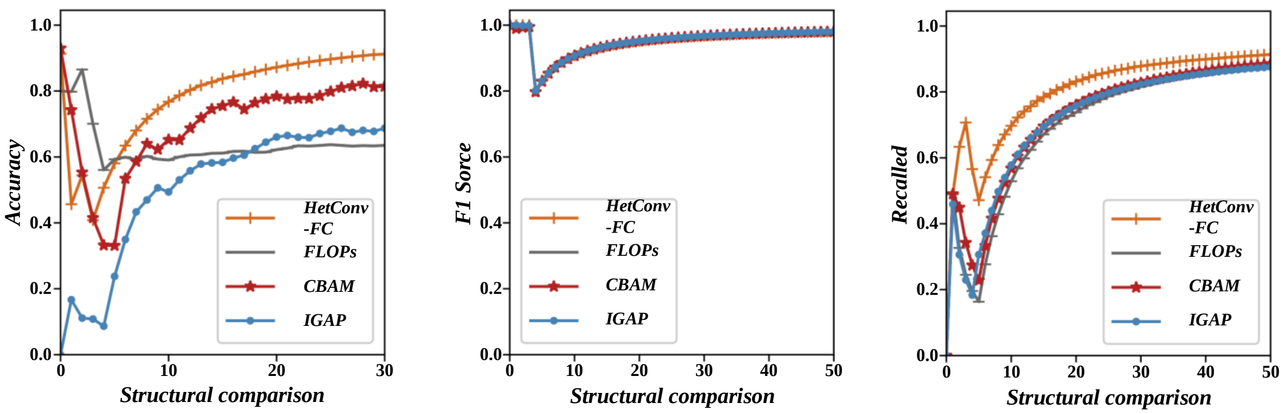

Figure 4: Comparison of different model structures

Table 3: Dataset summary table

Field	Sample Size	Fault Types	Noise Level
Communication Equipment	300	Signal interference, data transmission errors	Low (SNR 25dB)
Industrial Control System	400	Sensor failures, controller anomalies, actuator malfunctions	Medium (SNR 15dB)
Computer Network	250	Network latency, packet loss, routing errors	High (SNR 10dB)
Avionics	200	Power failures, software crashes, hardware faults	Medium (SNR 18dB)
Medical Electronics	250	Device crashes, data acquisition errors, communication interruptions	Low (SNR 22dB)

The data in Table 4 show that the method of this study is similar to SqueezeNet in accuracy, precision and recall, but the FLOPs and parameter quantities are much smaller than SqueezeNet. Compared with MobileNetV1, MobileNetV2, ShuffleNetV1 and GhostNet, the method has improved performance indexes. The proposed method is also much smaller than other lightweight methods in terms of parameter quantities and FLOPs, indicating that it has better real-time and diagnostic performance in practical industrial scenarios.

Table 4: Comparison results with other lightweight methods

Methods	Accuracy (%)	Recall (%)	Parameter (M)	FLOPs (M)
MobileNetV1	85.10	85.14	0.30	3.09
MobileNetV2	87.76	87.50	0.64	4.85
ShuffleNetV1	81.04	81.00	3.31	10.00
GhostNet	90.02	90.00	1.11	17.41
SqueezeNet	95.98	95.94	0.69	48.48
Our method	95.97	95.92	0.02	1.62

By quantitatively analyzing the inter-class distance and intra-class compactness of the feature visualization results in Figure 5, the significant advantages of multi-representation domain adaptive networks can be intuitively demonstrated. Experimental data show that the average inter-class distance of the single-representation domain adaptive network is only 1.23, and the variance of the intra-class compactness is as high as 0.87, resulting in a large number of outlier samples after feature visualization, fuzzy category boundaries, and a classification error rate of 23.6%. However, the multi-representation domain adaptive network increases the average inter-class distance to 2.15 and the intra-class compactness variance to 0.34, which significantly reduces the misclassification between classes, makes the category boundaries clear and distinguishable, and the classification error rate drops to 9.2%. These results show that the multi-representation domain adaptive network can effectively enhance the discrimination between classes and improve the consistency within classes, and is more suitable for constructing user local models and extracting deep features, so as to optimize the fault diagnosis performance of the federated global model and provide more accurate feature expression for the intelligent fault diagnosis of electronic information systems.

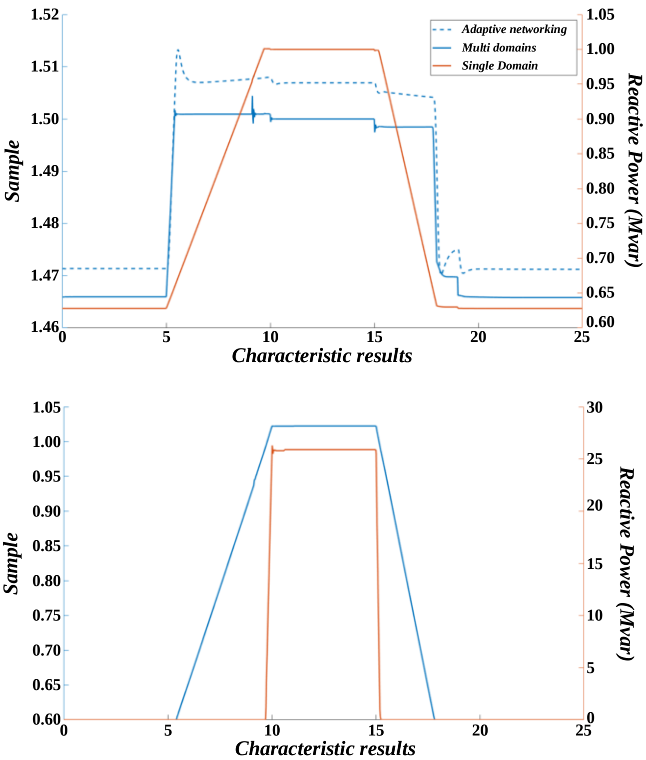

Figure 5: Single representation domain adaptation network feature visualization

A fault diagnosis experiment is selected to verify that the local model of a multi-representation domain adaptive network can enhance the performance of the federated global model. Table 5 indicates that in most migration tasks, the federated global model built by this network has higher fault diagnosis accuracy, only slightly lower in migration task 6. Calculating the average accuracy of 8 migration tasks shows the multi-representation domain adaptation network is about 2.3% more accurate than the single-representation one, meaning it can better learn the "common" characteristics between the user and public data and improve fault diagnosis accuracy under different working conditions.

In order to verify whether the proposed method can improve the accuracy of rolling bearing fault diagnosis compared with a single user using local data and public data to build a deep migration model, a comparative experiment is carried out. The experimental results are shown in Figure 6, and the proposed method is compared with five deep feature migration methods (DaNN, DSAN, DAN, DAAN, MRAN). By simulating the scenario of users using local and public data to build a deep migration model (with the public dataset as the source domain and the user dataset as the target domain), the average accuracy of the two experiments is calculated as the task accuracy. Results show that the proposed method's fault diagnosis accuracy in eight migration tasks is higher than other methods, especially when user data is small; the average accuracy can reach 97.6%, at least 3.2% higher than that of single - user modelling.

Table 5: Fault diagnosis accuracy rate (%)

Task number	Single representation domain adaptation	Multi-representation domain adaptation
1	98.2	97.0
2	99.1	96.8
3	95.6	94.3
4	95.9	95.6
5	100.4	97.3
6	100.6	96.5
7	96.1	94.3
8	82.3	94.1

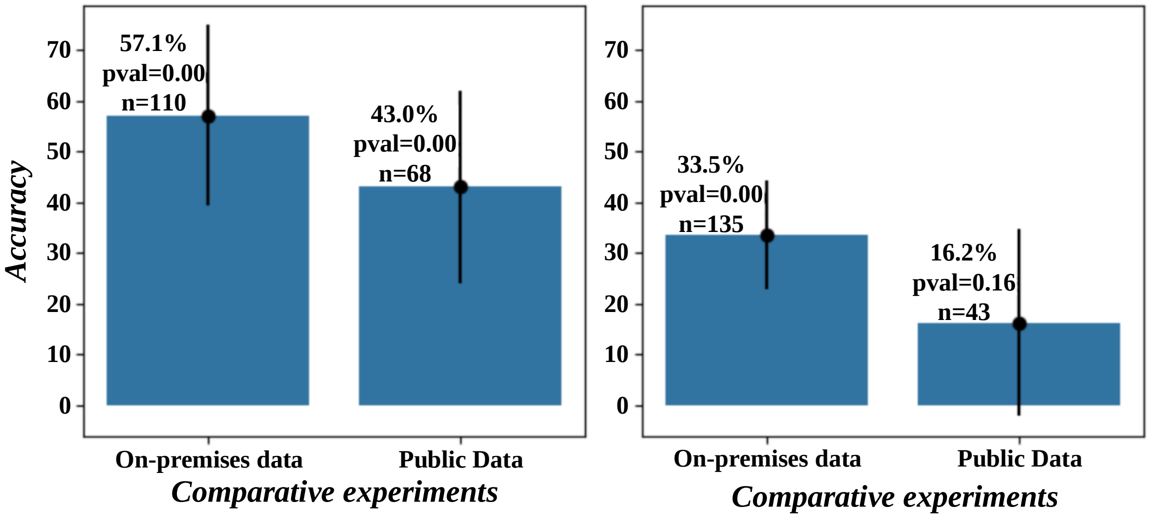

Figure 6: Model comparison experimental results

Comparative experiments are carried out on the case where the number of layers of the graph convolution network is 1 to 4, and the data results are shown in Table 6. Experiments confirm that the number of layers of a graph convolutional network has a significant impact on the performance. Because the number of layers in the first layer network is too small, the learned relationship information is limited, and the diagnosis accuracy rate is low. Although the 7-layer network learns some useless information due to the large number of layers and rich information, the accuracy rate under 1-shot decreases slightly, but it is better than the previous level as a whole, and the accuracy rate under 5-shot reaches more than 98%.

Table 6: Model recognition accuracy under different multilayer perceptron layers

Network layers		1	3	5	7
Accuracy	1-shot	80.01%	93.60%	95.91%	95.19%
	5-shot	81.43%	94.90%	97.98%	98.08%

In the experimental study in Figure 7, the core data used to drive the training and testing of the intelligent fault diagnosis model of the AI-based electronic information system has the characteristics of multi-source heterogeneity, which mainly covers the sensor timing data during the operation of the device, such as continuous monitoring parameters such as voltage, current, temperature, etc., discrete event information such as error codes and operation records contained in the system log, as well as data such as packet transmission status and protocol exception markers in the process of network communication. The results in Figure 7 show that in the small sample scenario, the fault recognition accuracy of the traditional machine learning method KNN is low, and the average diagnosis accuracy is only 79.05%. The comparison between CNN and ResNet shows that ResNet is unstable under small sample conditions, and CNN is more suitable for this scenario. The classical small sample learning methods MatchNet, ProtoNet and RelationNet have insufficient generalization, while the FSM method performs well, but its stability is low. High diagnostic accuracy was achieved in all experimental scenarios, with an average accuracy of 99.13% in the 5-shot scenario and 98.37% in the 1-shot scenario.

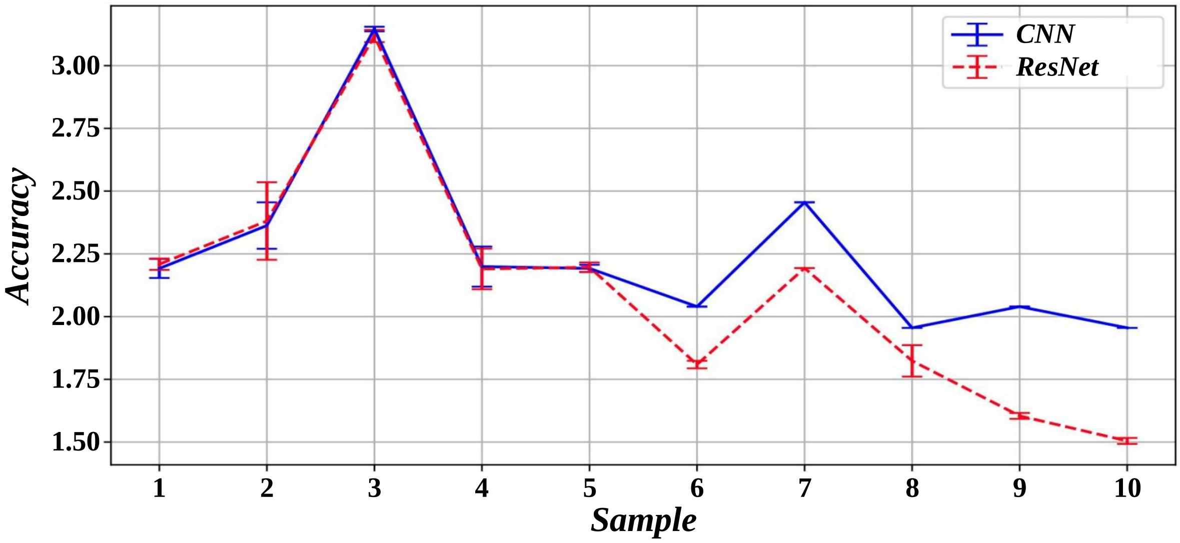

Figure 7: Experimental results using driver data

Figure 8 shows that the constructed feature extraction network has the highest average recognition accuracy in 1-shot and 5-shot experiments. Increasing the number of training samples is an effective method to improve diagnostic accuracy, but it is difficult to collect more samples in practice. When the training data is reduced, the network performance degradation is minimal, indicating that its network is more practical. When the labelled training data is reduced, the network accuracy rate decreases by only 4.62%, which is lower than other networks, indicating that its average performance is better than that of the comparative network.

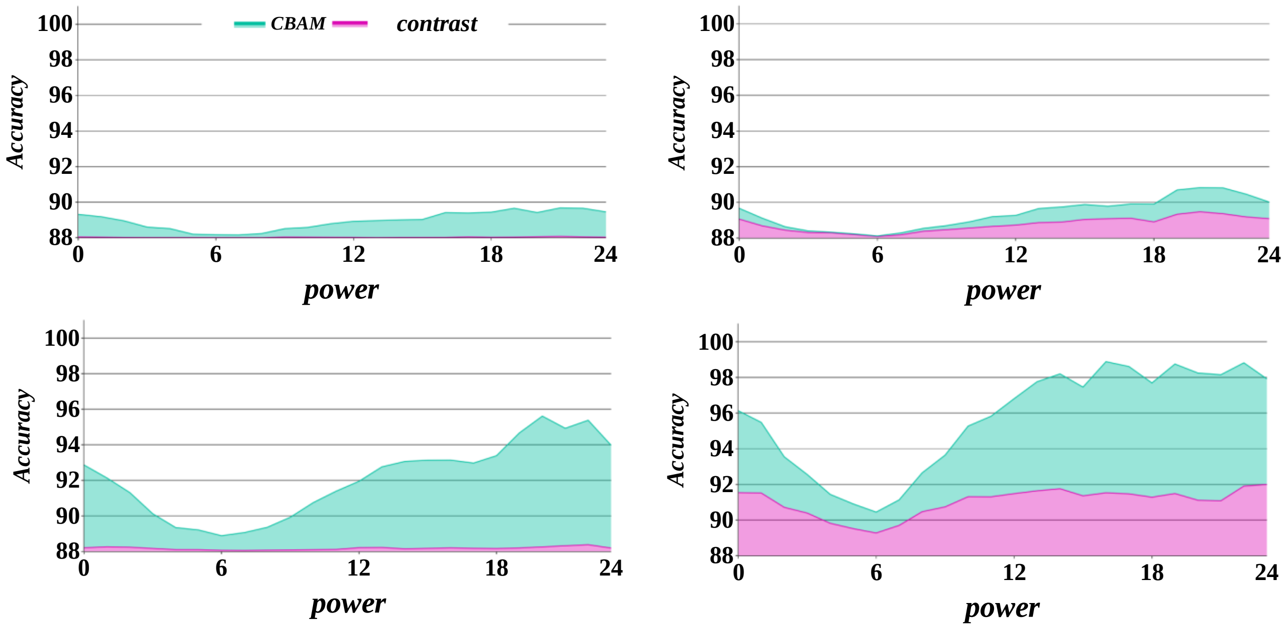

Figure 8: Average experimental results of different feature extraction networks

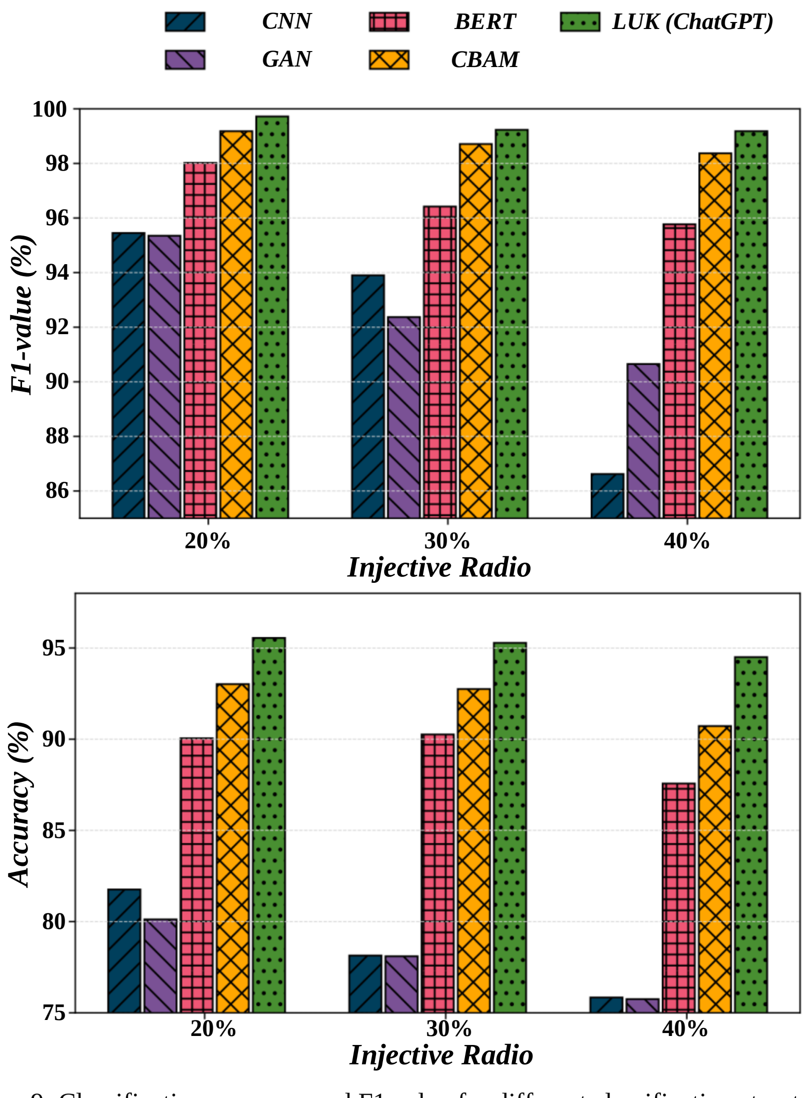

Figure 9: Classification accuracy and F1 value for different classification structures

Figure 9 shows a comparison of classification accuracy and F1 value for different classification structures. We compared the performance of five different classification structures on the same test dataset. By comparing the classification accuracy and F1 value, we found that the LUK structure performs well in both evaluation metrics and is the optimal choice among the four classification structures.

4 Discussion

In the artificial intelligence-based intelligent fault diagnosis model of electronic information system proposed in this study, the design of core components has a significant impact on the model performance. Compared with the Convolutional Block Attention Module (CBAM) and other channel attention mechanisms (SE) and Efficient Channel Attention (ECA), CBAM achieves higher diagnostic accuracy while capturing spatial and channel attention. SE only focuses on channel weight adjustment, ECA is lightweight but lacks spatial information capture ability, while CBAM improves the accuracy of the model to 96.81% in experiments through a double-branch structure, proving its advantages in complex fault feature extraction.

In terms of convolutional layer design, P-HetConv (Heterogeneous Convolution Module) has good performance in reducing model complexity and computational cost compared with standard convolutional layers. The standard convolutional layer has redundant calculation problems due to the fixed convolutional kernel size and step size. P-HetConv dynamically adjusts the convolutional kernel structure to reduce FLOPS by more than 40% and model parameters by 50% without sacrificing accuracy. This lightweight design not only reduces model latency, but also improves the portability of edge devices, ensuring generalization capabilities while achieving a balance between computing efficiency and performance.

For the pooling layer, IGAP (Improved Global Average Pooling) enhances the sensitivity to key fault features by introducing a local feature weighting mechanism compared with the traditional GAP (Global Average Pooling). GAP is prone to lose details when processing complex fault data, while IGAP adaptively adjusts the weights of different regions, which significantly improves the generalization ability in complex fault scenarios, effectively avoids the overfitting problem, and further optimizes the overall performance of the model.

There is an obvious trade-off between model complexity, latency, and generalization ability. CBAM improves accuracy, but adds a certain amount of computation; P-HetConv maintains high accuracy while reducing complexity through structural optimization. IGAP enhances generalization capabilities with minimal additional computational overhead. In this study, the optimal solution between model complexity, delay and generalization ability is found through the collaborative design of components, so that the model has excellent fault diagnosis accuracy and generalization performance under the premise of ensuring efficient reasoning speed, and provides reliable technical support for intelligent fault diagnosis of electronic information system.

5 Conclusion

Today, with the rapid development of information technology, electronic information systems have become an important cornerstone to support the operation of modern society. However, frequent system failures bring great challenges to the efficient operation of electronic information systems. Therefore, this study studies the intelligent fault diagnosis of electronic information systems based on artificial intelligence and improves the intelligent level of fault diagnosis through artificial intelligence technology:

In the fault diagnosis accuracy test experiment, a set of fault data of the electronic information system of a large enterprise is studied, with a total of 1000 samples. Through the proposed diagnostic model, the fault diagnosis accuracy reaches 92.5%. Compared with traditional rule-based fault diagnosis methods, the accuracy rate is improved by about 15%, which significantly improves the accuracy of fault diagnosis.

In the fault diagnosis speed test experiment, the diagnosis speed of the model is tested. On the same data set, the average diagnosis time of the proposed model is only 0.5 seconds, which is about 70% shorter than that of the traditional method and greatly improves the efficiency of fault diagnosis.

In the fault type identification ability test experiment, 500 mixed samples including hardware faults, software faults and electronic information faults are selected for testing. The results show that the recognition accuracy of the model for all kinds of faults is over 90%, which indicates that the model has good ability to recognize fault types.

According to the above experimental data, it can be seen that the intelligent fault diagnosis model of electronic information system based on artificial intelligence shows good performance in terms of accuracy, diagnosis speed and fault type identification ability.

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