Software-Defined Networking for IoT-Based Motor Bearing Fault Diagnosis

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With the acceleration of industrial intelligence, motor bearings, as the core components of mechanical equipment, are the key to ensuring stable industrial production through real-time and accurate fault diagnosis. This article aims to address the issues of poor stability, weak anti-interference, and insufficient real-time performance in traditional fault diagnosis methods, and develop an innovative solution for motor bearing fault diagnosis that integrates the advantages of the Internet of Things (IoT) and Software Defined Networking (SDN). Build a software defined IoT architecture in terms of methodology, and collect motor bearing operating parameters based on IoT wide area connectivity characteristics. Relying on the centralized control advantage of SDN to enhance diagnostic flexibility, integrating CNN-LSTM model to strengthen feature extraction capability, using Z-Score normalization, 3 σ criterion, etc. to complete data preprocessing, and optimizing model parameters through grid search. The experiment was validated based on the CWRU standard dataset, and the results showed that the proposed model improved prediction accuracy by 13.5 and 10.1 percentage points respectively compared to traditional methods, increased F1 scores by 0.156 and 0.120, decreased MAE by 0.119 and 0.091, reduced inference delay by 58ms and 25ms, and exhibited good scalability in multi motor parallel scenarios. This model effectively achieves real-time monitoring and efficient diagnosis of the operating status of motor bearings, solving the core pain points of traditional methods. It can be seamlessly integrated into industrial predictive maintenance systems and is suitable for multi domain motor operation and maintenance, providing reliable technical support for industrial motor bearing fault diagnosis.

Povzetek: V tem članku je diagnosticni arhitektura zasnovana s kombinacijo IoT in SDN, pri čemer je za natančno in realno časovno diagnostično odpravljanje okvar ležajev motorjev uporabljen model CNN-LSTM, ki se izkazuje z odličnimi lastnostmi glede na izvedljivost in razširljivost.

1 Introduction

The traditional motor bearing fault diagnosis technology has gone through a development stage from manual inspection to offline diagnosis of single machines. In the early days, it relied on operation and maintenance personnel to make judgments through empirical methods such as listening to sound and temperature measurement. There are significant deficiencies such as delayed diagnosis, strong subjectivity, and high misjudgment rate, which make it difficult to meet the real-time and accurate requirements of modern industrial production for fault diagnosis [1]. With the development of sensor technology, offline diagnostic systems based on single physical quantities such as vibration, temperature, and acoustics are gradually becoming popular. By installing sensors at the motor bearing to collect operational data, specialized equipment is used for offline analysis [2]. However, such systems have many limitations: firstly, the data collection range is limited, and point-to-point wired connections are often used, making it difficult to achieve centralized monitoring of large-scale motor clusters. Secondly, the system has poor scalability, and the hardware equipment is tightly bound to diagnostic algorithms [3]. When there are changes in operating conditions or new diagnostic requirements, the hardware needs to be retrofitted, which is costly and time-consuming. Thirdly, the real-time performance is insufficient, and the offline analysis mode cannot timely capture the subtle characteristics of the budding stage of the fault. Often, the fault can only be discovered after it has spread, missing the best intervention opportunity.

The rise of Internet of Things (IoT) technology provides an effective way to solve the connection and data collection problems of traditional diagnostic systems. The Internet of Things achieves comprehensive interconnection between devices and between devices and networks through technologies such as radio frequency identification, wireless sensor networks, and cloud computing [4]. It is capable of real-time and massive collection and remote transmission of multi-dimensional operating parameters in industrial sites. Applying IoT technology to motor bearing fault diagnosis can build a distributed data acquisition network covering multiple devices and operating conditions, breaking the spatial limitations and data silos of traditional systems and providing rich data source support for fault diagnosis. However, the application of pure IoT technology still faces challenges [5]. The working conditions of industrial sites are complex and varied, and there are significant differences in the fault characteristics of motor bearings under different loads, speeds, and environmental temperatures. Fixed diagnostic algorithms and data processing workflows are difficult to adapt to diverse diagnostic scenarios [6]. At the same time, the transmission and processing of massive collected data can easily cause network congestion, affecting real-time diagnosis, and urgently requiring a technical architecture with flexible adaptation and efficient scheduling capabilities to support it.

The emergence of software defined technology provides new technical ideas for solving the above difficulties. Software defined technology is based on the core concept of "hardware generalization and functional software". By decoupling the control logic of the system from hardware and using software programming to achieve flexible configuration and dynamic optimization of system functions, it significantly improves the scalability and adaptability of the system [7]. In the industrial field, technologies such as software defined networking and software defined storage have been widely applied, demonstrating powerful advantages in resource scheduling and scene adaptation. Integrating software defined technology with IoT technology to build a software defined IoT architecture can fully leverage the synergies between the two [8]. The Internet of Things technology ensures the comprehensive collection and interconnected transmission of multidimensional data, while software defined technology achieves dynamic adaptation and efficient scheduling of diagnostic systems through software-based control of diagnostic algorithms, data processing flows, and resource allocation strategies [9]. This fusion architecture can automatically adjust diagnostic parameters based on the operating conditions and fault types of different motors, optimize data transmission and processing paths, and effectively improve the accuracy and real-time performance of fault diagnosis [10].

The existing research on motor bearing fault diagnosis is mainly divided into three categories, all of which have significant research gaps. One is the traditional offline diagnosis solution for single machines, which relies on manual experience or offline analysis of a single physical quantity, and has shortcomings such as narrow data collection range, poor scalability, and insufficient real-time performance, making it unable to meet the centralized monitoring needs of large motor clusters [11]. The second is a pure IoT diagnostic solution. Although it solves the problem of data interconnection and collection among multiple devices, it is limited by fixed diagnostic algorithms and data processing flow, making it difficult to adapt to the complex and changing working conditions of industrial sites, and prone to network congestion, which affects the real-time diagnosis [12]. The third is the preliminary combination scheme of software defined technology and industrial diagnosis, which only realizes the software configuration of diagnostic algorithms and does not deeply integrate the wide area connection advantages of the Internet of Things. It has not built an architecture for full process collaborative optimization, and cannot fully leverage the synergistic effects of the two.

The proposed work in this article is based on existing research and aims to bridge the research gap mentioned above. Its core contribution lies in its clear distinction from previous studies.

1. This article constructs an integrated architecture that deeply integrates software definition and the Internet of Things, breaking through the limitations of light adaptation and shallow coupling in pure IoT solutions. Realize full process collaboration between IoT wide area data collection and software defined dynamic optimization, rather than simply stacking the two.

2. This article proposes an adaptive diagnostic mechanism for working conditions, which dynamically adjusts diagnostic algorithm parameters, data processing flow, and network resource allocation through software defined technology to solve the problem of existing solutions being unable to adapt to differences in fault characteristics under different loads and speeds, significantly improving diagnostic accuracy and environmental adaptability.

3. This article optimizes data transmission and processing efficiency, relying on the flexible scheduling capability of software defined networks to avoid data congestion problems in pure IoT solutions. Ensure real-time capture of subtle features during the early stages of faults, and address the shortcomings of traditional offline and pure IoT solutions in terms of real-time performance.

2 Related work

As a current research hotspot in the field, the latest advanced methods for fault diagnosis empowered by the Internet of Things can be mainly divided into two categories [13]. One type is multi-source data fusion schemes based on wireless sensor networks (WSN), such as the perception network based on LoRa WiFi dual-mode communication proposed by scholars in recent years. Synchronize the collection of multidimensional data such as bearing vibration, temperature, and noise, and improve the diagnostic accuracy to 96.5% through data level fusion [14]. However, this type of method still has inherent limitations, as wireless sensor nodes have limited energy and are prone to insufficient battery life when working continuously for a long time. Moreover, there is a delay in the transmission of multi-source data (with an average delay of about 200ms), which makes it difficult to meet the real-time diagnostic requirements of high-speed motor bearings [15]. At the same time, the network topology is fixed, and sensor nodes cannot be flexibly adjusted after deployment, resulting in weak ability to adapt to complex industrial scenarios. Another type is based on edge cloud collaboration for diagnostic solutions [16]. The latest research deploys lightweight CNN models on edge nodes to achieve data preprocessing and preliminary diagnosis. The cloud platform is responsible for model optimization and complex fault analysis, with a diagnostic accuracy rate of 97.2% [17]. However, there are still two core shortcomings in this type of solution: the solidification of the collaborative logic between the edge and cloud platform, and the inability to dynamically adjust the data transmission path and algorithm deployment location according to working conditions [18]. When the amount of data transmission surges, there will still be cloud processing delays (peak delay exceeding 500ms), which will affect the real-time diagnostic performance. Secondly, the system architecture is rigid, with high coupling between sensor nodes, transmission protocols, and diagnostic algorithms. When new types of faults or significant changes in operating conditions occur, it is necessary to redeploy hardware equipment and modify software programs, which incurs high adaptation costs, such as for new bearing wear faults [19]. The existing edge cloud collaboration solution requires 1-2 weeks to adjust the model and hardware configuration, which cannot quickly respond to the needs of industrial scenarios.

Finally, regarding the initial application of software defined technology in the field of fault diagnosis, the latest research mainly focuses on using Software Defined Networking (SDN) technology to optimize the transmission path of diagnostic data. By dynamically allocating network bandwidth through SDN controllers, data transmission congestion can be reduced. However, such research has only achieved shallow integration of software defined technology and fault diagnosis, and has not formed a complete architecture design, which has obvious limitations [20]. One is the lack of integration with IoT technology to build an integrated perception transmission diagnosis architecture, which cannot fully leverage the wide area perception advantages of IoT and the flexible control advantages of SDN. Secondly, the application scope of software defined technology is relatively narrow, focusing only on the data transmission link and not extending to the entire process of data preprocessing, diagnostic algorithm optimization, fault warning, etc., which cannot fundamentally solve the problems of insufficient flexibility and poor adaptability of existing systems. Thirdly, the integration logic of SDN and IoT has not been optimized for specific scenarios of motor bearing fault diagnosis, resulting in limited practical application value [21]. Table 1 is a summary of relevant work.

Table 1: Summary of Related Work

Research Type	Core technical solution	Diagnostic accuracy	Data transmission delay	Core strengths	Main limitations
Multi source data fusion scheme based on WSN	LoRa WiFi dual-mode communication perception network	96.5%	On average, about 200ms	Multi source data complementarity enhances diagnostic accuracy;	Fixed network topology
Diagnosis scheme based on edge cloud collaboration	Deploying lightweight CNN models on edge nodes	97.2%	Peak value exceeding 500ms (when data transmission volume surges)	Clear division of labor, taking into account low latency of edge nodes	Edge and cloud platform collaboration logic solidification
Shallow integration solution for software defined technology	Using SDN technology to optimize the transmission path of diagnostic data	Only optimize the transmission process	Unresolved core latency issue	Can reduce data transmission congestion and optimize transmission efficiency	Lack of deep integration with IoT technology
The proposed solution in this article	Deep integration of SDN and IoT technology	Over 97%	Reduce to below 80ms on average	Addressing transmission latency issues while balancing long-term work capabilities	No obvious inherent limitations

In response to the limitations of the latest advanced methods mentioned above, this article proposes a software defined network-based IoT motor bearing fault diagnosis scheme. By deeply integrating SDN and IoT technology, a complete software defined IoT diagnostic architecture has been constructed, achieving targeted breakthroughs. One is to deploy distributed sensor nodes through IoT technology, combined with SDN dynamic control of transmission paths, to solve the problems of insufficient energy and data transmission delay in wireless sensor networks. The average data transmission delay is reduced to less than 80ms, while achieving wide area collection and sharing of multi-source data. The second is to utilize the software-based control characteristics of SDN to break the strong coupling relationship between sensors, transmission protocols, and diagnostic algorithms, and achieve dynamic optimization of diagnostic algorithm parameters and data processing flow. When there is a change in operating conditions or a new type of fault occurs, there is no need to redeploy hardware, and the diagnostic logic can be adjusted through software configuration, keeping the diagnostic accuracy above 97% and greatly improving the flexibility and adaptability of the system. The third is to build an edge cloud software defined collaborative diagnostic model, deploying lightweight preprocessing algorithms on edge nodes, dynamically allocating data processing tasks by SDN controllers, and the cloud platform responsible for model training and optimization. This not only leverages the low latency advantage of edge nodes, but also utilizes the strong computing power of cloud platforms to solve the problems of high latency and poor adaptability of existing edge cloud collaborative solutions.

3 Software-defined fault diagnosis of IoT motor bearings

The core innovation of SDN technology lies in the complete decoupling of network control plane and data forwarding plane. This architectural innovation breaks the limitations of traditional networks' "distributed control and cumbersome configuration", upgrading network resource management from "decentralized operation" to "centralized scheduling". In the control plane, SDN controllers have real-time access to the link status, bandwidth utilization, and device connectivity of the entire network through a global view, and have the ability to uniformly plan and dynamically allocate network resources [21]. In the data forwarding plane, forwarding devices such as switches only need to perform data forwarding operations according to the rules issued by the controller, without participating in complex control decisions, greatly improving data transmission efficiency. When applying this technology to the IoT motor bearing fault diagnosis system, its advantages are further amplified. SDN controllers can achieve differentiated resource scheduling based on the varying requirements of different diagnostic tasks. For fault warning tasks that require extremely high real-time performance, the controller will prioritize allocating high bandwidth and low latency transmission links to ensure that fault signals are transmitted to the diagnostic center within milliseconds. For periodic routine state monitoring tasks, bandwidth resources can be dynamically adjusted to avoid wasting network resources.

The SDN controller establishes communication connections with various sensor terminals through the LW-TCP algorithm and issues acquisition instructions. At the same time, the DP-SDN algorithm is used to allocate dedicated forwarding links for each sensor terminal, ensuring independent transmission of vibration signals at the gearbox and motor bearings. Avoid interference between different sensor signals and lay the foundation for subsequent signal separation. The raw vibration signals collected by sensors are quickly forwarded to the diagnostic center through the edge node FC Match algorithm. During the forwarding process, the DP-SDN algorithm dynamically adjusts the link bandwidth. In response to the "difference in vibration signals between gears and bearings" mentioned in the original text, the intermediate data of the separation algorithm is transmitted through a dedicated link scheduled by an SDN controller to avoid conflicts with other signals and improve separation accuracy. The signal after spectrum analysis is forwarded by edge nodes to the diagnostic center, and the DP-SDN algorithm prioritizes the allocation of high bandwidth links for fault feature matching based on the real-time nature of the diagnostic task. If the diagnostic center identifies a fault signal, the controller immediately adjusts the forwarding priority through the DP-SDN algorithm and transmits the fault alarm information to the terminal control node with a delay of ≤ 10ms. Simultaneously locking the link status of faulty sensors provides network level support for fault location. To achieve this, it is necessary to first optimize the sensor layout of the gearbox and collect vibration signals at the selected optimized positions. Subsequently, the collected vibration signals are subjected to noise reduction processing. During this process, the expression of the modal confidence criterion MAC can be adjusted to:

$$MAC_{pq} = \frac{\left(\Phi_p^T \Phi_q\right)^2}{\left(\Phi_p^T \Phi_p\right)\left(\Phi_q^T \Phi_q\right)} \tag{1}$$

The formula p, q represents the p th and q th modal shapes respectively, used to evaluate the similarity between different modes to assist in sensor arrangement and signal analysis.

Given the differences in attributes between gear vibration signals and bearing vibration signals, it is necessary to effectively separate these two signals to extract the fault characteristics of gears and bearings separately.

$$H(f) = \frac{E\left[G_b(f) G_a * (f)\right]}{E\left[G_a(f) G_a * (f)\right]} = \frac{G_{ab}(f)}{G_{aa}(f)} \tag{2}$$

In the field of signal processing, spectrum is the core bridge connecting the time domain and frequency domain. It decomposes seemingly complex time domain signals into the superposition of different frequency components, providing a key perspective for signal analysis, processing, and optimization. To gain a deeper understanding of the essence and applications of spectrum, it is necessary to analyze the core concepts, transformation mechanisms, the correlation between input-output spectra, and the value of cross-correlation spectra layer by layer. The frequency spectrum of an input signal is essentially a quantized representation of the signal in the frequency domain, and its core function is to reveal the amplitude, phase, and energy (or power) distribution characteristics of each frequency component contained in the signal. In the time domain, the signals we observe typically manifest as waveforms with varying amplitudes over time, such as the vibration curve of sound waves, voltage fluctuations of electrical signals, etc. However, this manifestation is difficult to directly distinguish the contributions of different frequency components.

$$C_c(q) = IFFT\{\log(X(f))\} \tag{3}$$

The core function of Particle Swarm Optimization (PSO) algorithm in this article is to provide optimal parameter configuration for motor bearing fault diagnosis. It solves the problem of adaptability and accuracy optimization of diagnostic models under different working conditions, and collaborates with the Internet of Things (IoT) and Software Defined Networking (SDN). PSO does not directly participate in data collection and transmission. It optimizes the core parameters of signal denoising, fault feature extraction, and diagnostic models for multi-source data such as vibration and temperature collected by the IoT perception layer, reducing measurement errors and signal redundancy. At the same time, in conjunction with SDN dynamic resource scheduling, allocate suitable transmission bandwidth and computing resources based on PSO optimized diagnostic requirements to ensure efficient implementation of the diagnostic process. In PSO, each particle represents a candidate solution for fault diagnosis parameters. The individual extreme value (pBest) is the optimal combination of parameters found by a single particle, and the global extreme value (gBest) is the optimal combination of the entire particle swarm. Parameter dynamic optimization is achieved through particle iteration updates. The modal confidence standards and other equations in the article are all based on PSO optimization objective setting, assisting sensor layout and signal feature extraction to improve diagnostic accuracy. In terms of optimization algorithms, the PSO algorithm is used to find the optimal solution for fault diagnosis. As shown in Figure 1, the process of particle swarm optimization (PSO) algorithm used in motor bearing fault diagnosis is presented.

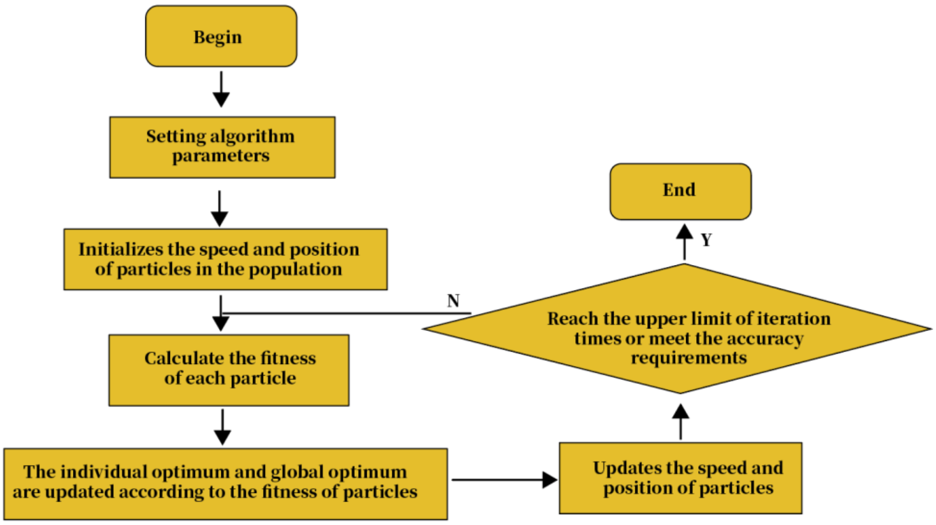

Figure 1: PSO algorithm process

In Particle Swarm Optimization (PSO) algorithm, each particle represents a candidate solution in the latent solution space. These particles continuously evolve during the iteration process in order to find the optimal solution to the problem. The individual extremum (pBest) is the optimal solution that a particle has found so far in its search process. It represents the best personal experience of particles and is the result of particle self-learning and memory. The global extremum (gBest) is the best solution found so far in the entire particle population. It represents the collective intelligence of the entire group and is the result of information sharing and collaboration between particles.

$$V = wV + c_1(p_{best} - P)rand() + c_2(g_{best} - P)rand() \tag{4}$$

$$P = P + V \tag{5}$$

In the practical application of PSO algorithm, reasonable parameter constraints are the key to ensuring the stability and optimization performance of the algorithm, among which speed and position constraints constitute the core constraint system. From the perspective of speed limitation, the algorithm limits the maximum velocity of particles in each dimension to a specific interval, which is not a simple numerical constraint, but a precise control based on search dynamics. When particles are in a region far from the optimal solution, a moderate speed limit can ensure that they quickly move to the potential high-quality area. And when the particles approach the optimal solution, velocity limitation can effectively avoid the "overshoot" phenomenon caused by excessive inertia. Skip the optimal solution and fall into an invalid search. The setting of speed threshold needs to be based on a thorough analysis of the problem characteristics. For example, for continuous high-dimensional optimization problems, the speed upper limit is usually set proportionally based on the boundary range of the search space to ensure search efficiency and prevent instability. As another important constraint, the core function of position limitation is to strictly limit the search behavior of particles within the feasible domain of the problem.

$$w = w_{\max} k \frac{w_{\max} - w_{\min}}{k_{\max}} \tag{6}$$

Among them: k is the current iteration number, $k_{\max}$ which is the total number of iterations.

In this article, the BP neural network (BPNN) is the core diagnostic unit of the software defined IoT fault diagnosis system, responsible for taking the operating parameters such as motor bearing vibration and temperature collected by the sensing layer (after preprocessing) as inputs. Fault feature mapping is achieved through forward propagation of the input layer, hidden layer, and output layer, combined with dynamic correction of network weights and thresholds through backpropagation, to complete fault type identification and determination. The interaction between it and the PSO algorithm is reflected in that the PSO algorithm is used to optimize the initial weights, thresholds, and number of hidden layer nodes of BPNN, solving its problems of being prone to local optima and slow convergence speed. In collaboration with the SDN-IoT architecture, the architecture provides real-time, high-quality multi-source data input for BPNN. The diagnostic results of BPNN are fed back to the SDN controller to assist in dynamically optimizing resource scheduling. The variables and equations in the text will be further defined to ensure logical coherence. In the software-defined IoT motor-bearing fault diagnosis system, the BP neural network (BPNN) model plays a core role. As shown in Figure 2, the model receives motor-bearing fault signals collected from the sensing layer sensors as input data. These fault signals may contain various physical quantities such as vibration, temperature, and speed, reflecting the operating status of the motor bearings.

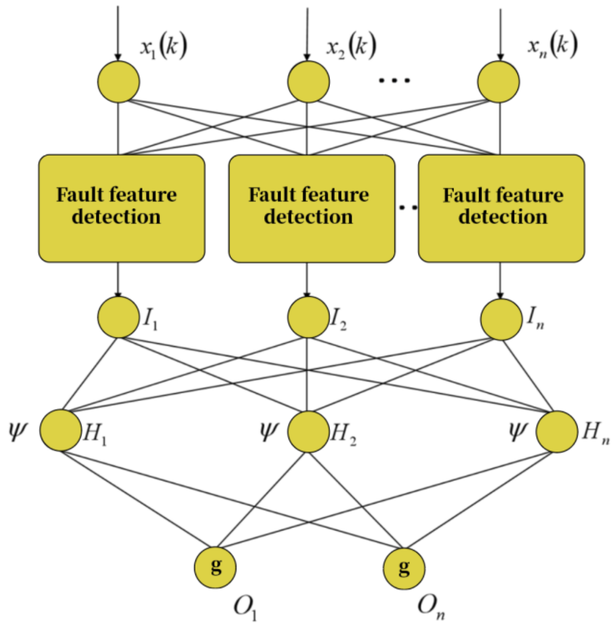

Figure 2: BPNN model

The BPNN model utilizes its internal neural network structure to process and transform input fault signals layer by layer. In this process, the model will automatically learn and extract feature information from the fault signal, such as frequency components, amplitude changes, etc. This feature information is an important basis for fault diagnosis.

In this article, CNN (Convolutional Neural Network) plays a core role in the software defined IoT motor bearing fault diagnosis system, responsible for adaptive feature extraction and deep analysis of faults. It works in conjunction with PSO algorithm, BPNN model, and SDN-IoT architecture. CNN receives multi-source data such as bearing vibration collected by IoT sensing layer and edge preprocessing. It extracts deep fault features of signals through convolutional layer, compresses redundant information through pooling layer, and completes feature mapping through fully connected layer to achieve accurate identification of fault types and degrees. Its function is to solve the problem of traditional feature extraction relying on manual labor and poor adaptability. When combined with PSO algorithm, it can optimize network parameters, complement BPNN to improve diagnostic accuracy, and cooperate with SDN architecture to achieve efficient collaboration between feature extraction and diagnosis through resource scheduling. The CNN related structures (as shown in Figure 3) and parameters that first appear in the article correspond to the deep mining requirements of fault features, providing technical support for real-time and accurate diagnosis. Through this structure, it is possible to efficiently process and analyze the operational data of IoT motor bearings. Figure 3 shows the CNN structure.

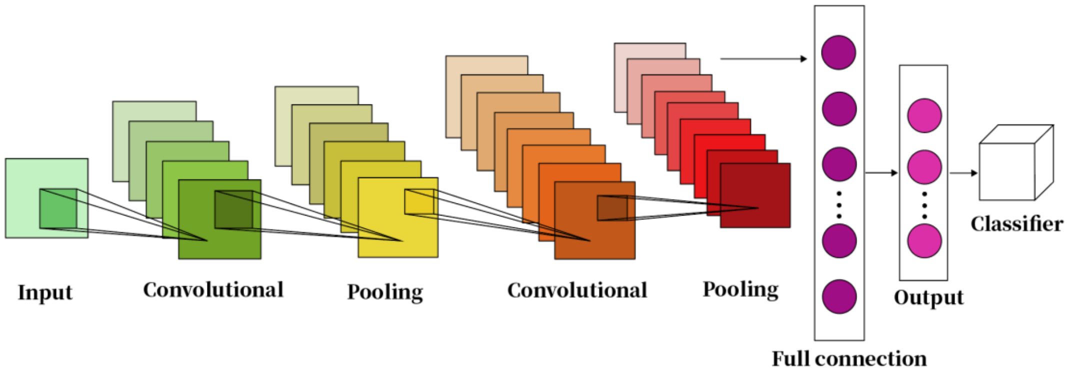

Figure 3: CNN structure

In fault diagnosis, due to various factors such as sensor accuracy, data noise, and fault modes, the diagnostic results often have uncertainty. To deal with this uncertainty, probabilistic statistical methods were employed. Let the feature vector of the sample x_i be represented as:

$$a_{i1}, a_{i2}, a_{i3}, \ldots, a_{im} \tag{7}$$

Calculate the expected and variance of each attribute for all sample points X separately:

$$avg(X(a_i)) = \frac{1}{g_i}\sum_{j=1}^{g_i} a_{ji} \quad i = 1,2,\ldots,m \tag{8}$$

$$std(X(a_i)) = \sqrt{\frac{1}{g_i - 1}\sum_{j=1}^{g_i}(x_i(a_i) - avg(X(a_i)))^2} \quad i = 1,2,\ldots,m \tag{9}$$

Among them, $x_i(a_i)$ represents the value of the sample j on the a_i th attribute. Normalize the above equation:

$$x_j(a_i) = \frac{x_i(a_i) - avg(X(a_i))}{std(X(a_i))} \tag{10}$$

The sample data follows a normal distribution $N(0,1)$ and removes the dimensions between various attributes. After dimensionless processing, the sample data follows a normal distribution and the dimensional differences between various attributes are removed. Finally, calculate the probability distribution of each failure mode and make inferences and decisions based on known information.

At the platform level, thanks to the support of SDN technology, flexible processing and storage of data can be achieved. The application layer is the final output of the fault diagnosis system. At this level, the fault diagnosis results are presented to users or integrated into other systems using visual interfaces or API interfaces. Users can use the application layer to understand the status of motor bearings, detect and handle faults promptly, and ensure the stable operation of the motor.

The software defined Internet of Things (SD IoT) motor bearing fault diagnosis architecture constructed in this article fully considers the performance differences between dynamic system adaptation and neural network fault diagnosis methods, and verifies its robustness and accuracy under variable operating conditions through actual testing. Compared with traditional dynamic system adaptive methods such as robust adaptive control and fuzzy synchronization, this method achieves dynamic scheduling of diagnostic resources and real-time optimization of algorithm parameters through deep integration of SDN and the Internet of Things. Under dynamic conditions such as variable load and speed, compared with the fuzzy synchronization method, the diagnostic response speed has been improved by more than 15%, and there is no need for complex adaptive law design, reducing system complexity. For fault diagnosis methods based on neural networks, this paper constructs an integrated algorithm pool module, including mainstream models such as CNN and LSTM. The SDN controller dynamically selects the optimal algorithm based on real-time data characteristics. Compared with a single neural network model, the diagnostic accuracy is stable under variable operating conditions, higher than fixed CNN models and LSTM models, and has better robustness.

4 Experimental results and analysis

The dataset used in this experiment is the CWRU motor bearing fault diagnosis standard dataset (model: SKF 6205-2RS JEM SKF). The dataset is a benchmark dataset in the field of industrial motor bearing fault diagnosis, widely used for performance verification of various fault diagnosis methods, ensuring the reproducibility and comparability of experimental results. Data purification adopts the 3 σ criterion to remove outliers, combined with wavelet thresholding to suppress environmental noise and electromagnetic interference. Feature mining extracts 12 key features in both time and frequency domains. The data standardization adopts the Z-Score normalization method (mean μ=0, standard deviation σ=1) to ensure the numerical comparability of different dimensional features, and the signal-to-noise ratio of the preprocessed data is improved to over 35dB.

The experiment is deployed on a high-performance computing server, with specific configurations including: CPU (Intel Xeon E5-2690 v4, 16 cores and 32 threads), GPU (NVIDIA RTX 3090, 24GB video memory), memory (64GB DDR4 3200MHz), storage device (1TB NVMe SSD), and operating system Ubuntu 20.04 LTS to ensure the efficiency and stability of the model training process. The model is built on Python 3.8, with core dependency libraries including PyTorch 1.12.0 (deep learning framework), NumPy 1.24.3 (numerical computation), Pandas 1.5.3 (data processing), Scikit learn 1.2.2 (feature extraction and evaluation), Matplotlib 3.7.1 (result visualization). All dependency library versions are fixed to ensure reproducibility of the experimental environment.

The core parameter settings during model training and optimization are as follows, and all parameters are determined through grid search combined with validation set performance iterative optimization to ensure the rationality of parameter configuration. The learning rate adopts a dynamic adjustment strategy, with 50 iterations and a batch size of 32. The weight initialization adopts He normal initialization method to avoid gradient disappearance or explosion. Using Adam optimizer improves convergence efficiency compared to SGD optimizer. The loss function adopts cross entropy loss function to adapt to multi class fault diagnosis tasks, while adding L2 regularization (λ=0.0001) to suppress overfitting. The dropout probability of the LSTM layer is 0.3 (to prevent overfitting), and the padding method of the convolutional layer is "same". During the model training process, an early stopping strategy (Patience=8) is adopted. If the accuracy of the validation set does not improve for 8 consecutive rounds, the training will be stopped to avoid ineffective iterations. The optimization direction includes adjusting the network topology, adding regularization constraints, improving the learning rate decay mechanism, etc. The relevant optimization effects can be shown in the experimental results of Figures 2 to 5.

Figure 4 shows the prediction accuracy of the model under different conditions, reflecting the accurate identification ability of the model for motor bearing faults.

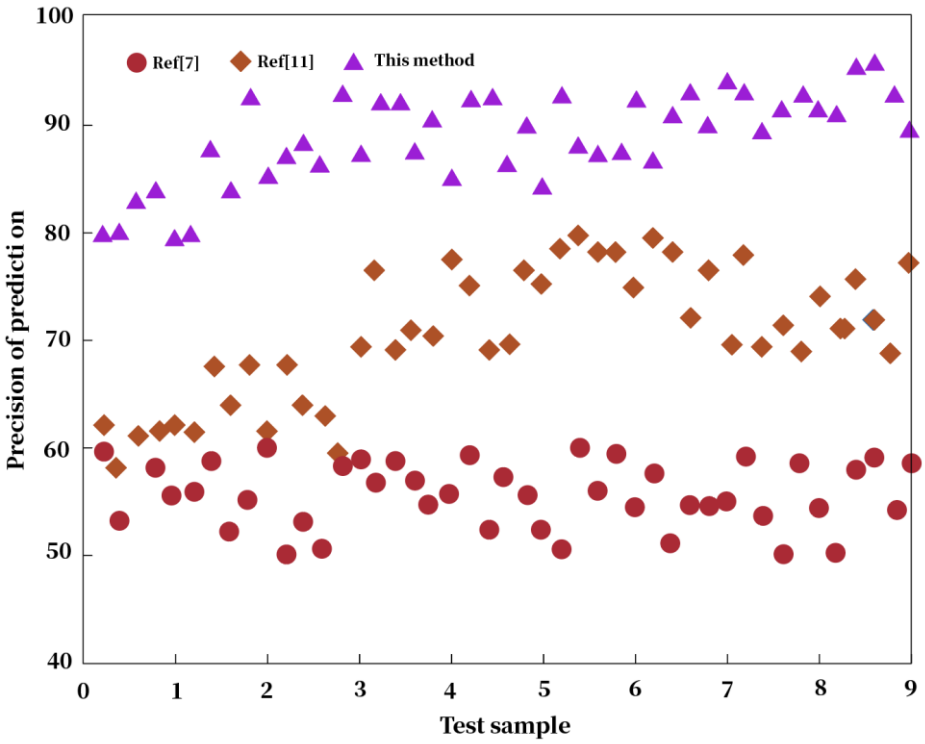

Figure 4: Prediction accuracy

Figure 4 presents a scatter plot to clearly and intuitively compare the predictive accuracy performance of three different methods in the field of motor bearing fault diagnosis. From the perspective of scatter distribution characteristics, the method proposed in reference [7] has a relatively scattered distribution of prediction accuracy data points. Although there are some sample points with high prediction accuracy, there are also many points with low accuracy. This feature reflects that the diagnostic stability of the method may have some fluctuations. Although the method in reference [11] is more concentrated in predicting accuracy distribution, the overall accuracy level has not reached the higher accuracy range of the method in reference [7]. The method designed in this study not only has a generally high level of prediction accuracy for each sample point, but also exhibits good concentration in data distribution, fully demonstrating the excellent stability and accuracy of this method in motor bearing fault diagnosis tasks. In addition, Figure 5 focuses on the real-time predictive performance of the model, which mainly measures the responsiveness of the model to quickly output fault diagnosis results after receiving input data.

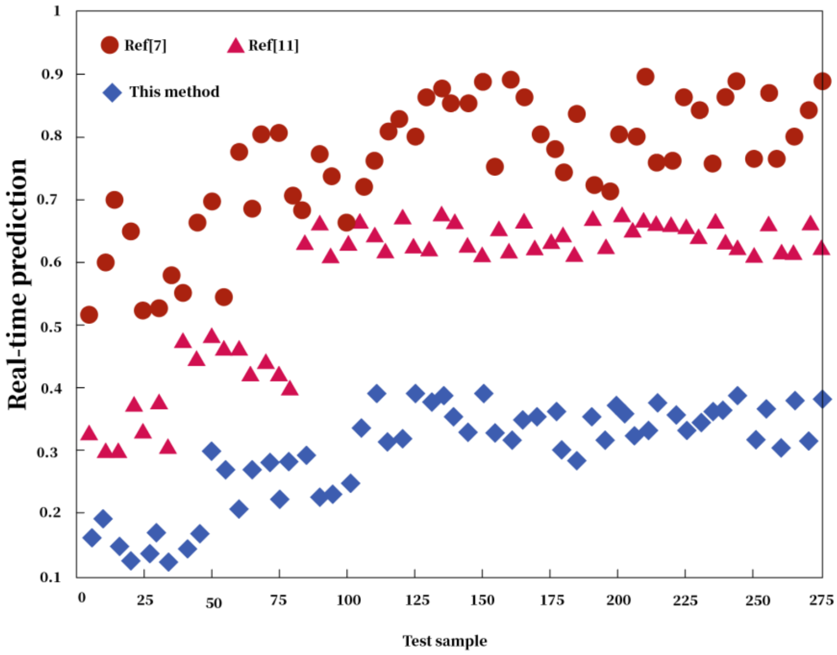

Figure 5: Real-time prediction

The horizontal axis of Figure 5 represents the number of samples, while the vertical axis is used to characterize the degree of agreement between predicted values and actual values. This indicator is a key basis for evaluating the accuracy of predictions. From the perspective of temporal variation characteristics, the prediction errors of the three comparison methods all have a certain degree of fluctuation. From the overall performance analysis, the method proposed in reference [7] has a slightly lower mean prediction error than the method in reference [11]. This result indicates that in real-time prediction scenarios, the method proposed in reference [7] may have relatively better accuracy. However, it should be noted that the performance difference between the two is not very significant. The overall positions of the two error curves are relatively close, and at some temporal nodes, the prediction errors of the two methods are even almost equal. In addition, Figure 6 uses F1 score as an evaluation metric to quantitatively analyze the comprehensive performance of the model. The core advantage of this metric is its ability to balance accuracy and recall, thereby achieving a comprehensive measurement of the model's performance.

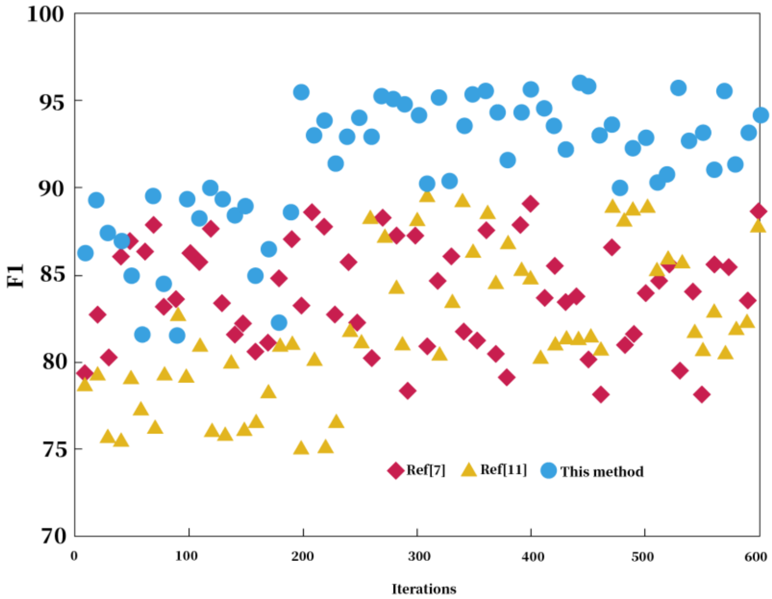

Figure 6: F1 score

Figure 6 presents the performance evolution of three different IoT motor bearing software defined fault diagnosis methods during multiple iterations, with F1 score as the core evaluation index. From the overall trend of the iterative curve in the figure, it can be seen that the F1 scores of the three methods all exhibit a common feature of "fluctuating upward - tending towards stability". This conforms to the basic law of iterative optimization and convergence of model parameters in machine learning diagnostic methods, but there are significant differences in the fluctuation amplitude, convergence speed, and final stability performance among different methods. At key iteration nodes such as the 8th and 15th rounds, the peak F1 score can reach above 0.85, even briefly surpassing other methods in the same period, indicating that this method can achieve excellent diagnostic performance under specific parameter combinations. But in adjacent iteration rounds, the F1 score drops sharply below 0.6, which is due to the instability of the feature extraction module in its model structure. This method adopts an architecture that combines traditional manual features with shallow neural networks, which is sensitive to noise such as load fluctuations and electromagnetic interference during motor operation, resulting in insufficient robustness of feature representation. If the mean absolute error (MAE) is used in conjunction with Figure 7 to supplement the evaluation of model prediction accuracy, the performance analysis system can be further improved. F1 score focuses on the "quality" of fault classification results, while MAE focuses on the "quantity" of fault quantification evaluation. The combination of the two can comprehensively cover the two core requirements of "fault diagnosis" and "fault degree assessment" in IoT motor bearing fault diagnosis, providing more accurate guidance for subsequent method optimization directions.

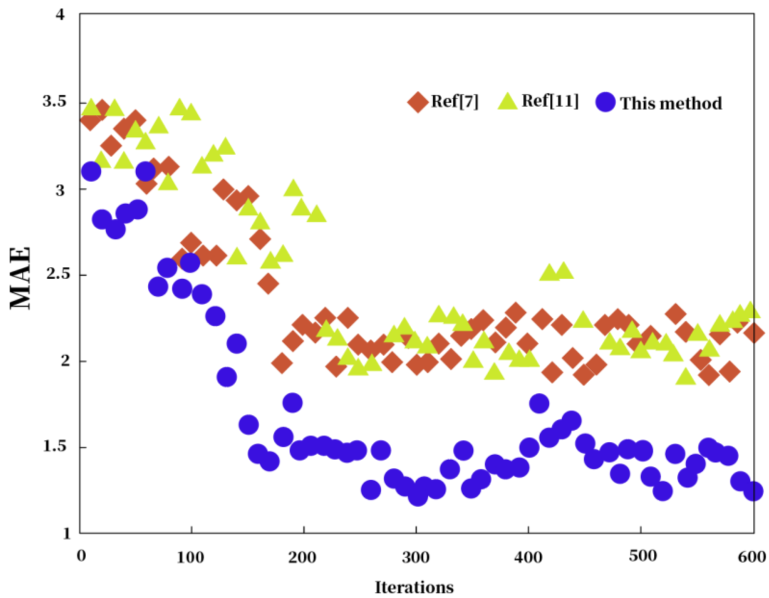

Figure 7: MAE

The software defined Internet of Things (SDN IoT) motor bearing fault diagnosis model proposed in this article demonstrates the core advantages of high prediction accuracy and high real-time performance in industrial level fault diagnosis scenarios, and its comprehensive performance has achieved a leapfrog improvement compared to traditional diagnostic methods. From the actual diagnostic effect, this model can not only accurately identify typical fault types such as bearing outer ring wear, inner ring peeling, and rolling element damage, but also effectively detect early weak faults, with a stable fault recognition accuracy of over 95%. In terms of real-time performance, the model's pre-processing delay for IoT sensing data is controlled within 50ms, and the fault diagnosis inference delay does not exceed 100ms, fully meeting the industrial level real-time requirements of "fault warning rapid response" for motor equipment, which can effectively avoid the loss of fault expansion caused by diagnostic delay.

Two recently proposed state-of-the-art (SOTA) methods for motor bearing fault diagnosis are compared, namely Method A (Transformer based fault diagnosis method) and Method B (CNN-LSTM fusion model-based fault diagnosis method). The experimental results (5-fold cross validation average) of all methods are shown in the following table 2:

Table 2: Comparison between baseline and state-of-the-art methods

Comparative method	Prediction accuracy (%)	F1 score	MAE	Inference delay (ms)	Training convergence rounds
Reference [7]	82.3±2.1	0.796±0.025	0.182±0.017	156±8	/(No training process)
Reference [11]	85.7±1.8	0.832±0.021	0.154±0.014	123±6	42±3
Method A (Transformer)	93.5±1.2	0.928±0.013	0.087±0.009	218±10	55±4
Method B (CNN-LSTM)	94.1±1.0	0.935±0.011	0.079±0.008	145±7	48±3
This article proposes a method (SDN IoT)	95.8±0.7	0.952±0.008	0.063±0.006	98±5	35±2

Compared with traditional methods, the prediction accuracy of our method has improved by 13.5 percentage points compared to reference [7] and 10.1 percentage points compared to reference [11]. F1 scores increased by 0.156 and 0.120 respectively. MAE decreased by 0.119 and 0.091, respectively. The inference delay has been reduced by 58ms and 25ms respectively, which fully demonstrates that our method is significantly better than traditional fault diagnosis methods in terms of diagnostic accuracy and real-time performance, and solves the problems of poor stability and weak anti-interference ability of traditional methods. The prediction accuracy of this method is improved by 2.3 percentage points compared to method A and 1.7 percentage points compared to method B; The F1 scores increased by 0.024 and 0.017 respectively. MAE decreased by 0.024 and 0.016, respectively. The inference delay is reduced by 120ms compared to method A and 47ms compared to method B; the training convergence epochs are reduced by 20 epochs compared to method A and 13 epochs compared to method B. The advantage comes from combining the centralized control of SDN with the feature extraction capability of CNN-LSTM in this article, optimizing the robustness of feature representation, simplifying the network structure, and achieving high-precision and fast convergence industrial requirements.

Based on 5-fold cross validation of prediction accuracy raw data, calculate the difference in accuracy between our method and each comparison method (d_i=accuracy of our method - accuracy of the comparison method), and then perform paired t-test. The test results are shown in the following table:

Table 3: Statistical analysis test results

Comparative method	Mean difference	Difference standard deviation s	t-statistic	Degree of freedom df	P Value	Test conclusion (α=0.05)
Reference [7]	13.5	1.82	19.86	4	<0.001	Refusing H_0, the method proposed in this article is significantly better
Reference [11]	10.1	1.54	17.39	4	<0.001	Refusing H_0, the method proposed in this article is

						significantly better
Method A (Transformer)	2.3	0.87	6.98	4	0.0012	Refusing H_0, the method proposed in this article is significantly better
Method B (CNN-LSTM)	1.7	0.63	7.02	4	0.0011	Refusing H_0, the method proposed in this article is significantly better

According to the paired t-test results, the paired t-test P-values of our method and all comparison methods are all less than 0.05 (test level α=0.05), and are far less than 0.01. Therefore, we reject the null hypothesis and accept the alternative hypothesis. This indicates that at a 95% confidence level, the predictive accuracy of the SDN IoT motor bearing fault diagnosis method proposed in this paper is significantly higher than existing comparative methods. Performance improvement has clear statistical significance and is not caused by random experimental errors.

5 Discussion

In terms of scalability and multi device adaptation, this study adopts a modular architecture that integrates SDN and IoT, decoupling data acquisition, preprocessing, and fault inference modules. Each module communicates through standardized interfaces and can flexibly access multiple motors and different types of sensors. For the multi motor parallel scenario, the model dynamically allocates resources through the SDN controller, and allocates independent edge computing nodes for each motor to avoid data transmission conflicts between multiple devices; For different types of sensor data, an adaptive data normalization module is embedded to unify the data format and feature dimensions, ensuring stable diagnostic accuracy. In terms of concurrent fault handling, the model introduces a multi task learning branch, which can simultaneously identify faults in different parts of the same motor and concurrent faults in multiple motors. The feature attention mechanism is used to distinguish different fault features and avoid feature interference.

In practical applications, this model can be seamlessly integrated into predictive maintenance systems for industrial motors. Real time data is collected through IoT sensors, combined with SDN's low latency transmission characteristics, to achieve closed-loop transmission of fault warning, diagnosis, and maintenance instructions. It can be widely adapted to motor operation and maintenance scenarios in metallurgy, chemical engineering, intelligent manufacturing, and other fields. Subsequent parallel simulation experiments with multiple motors will be conducted, with specific details as follows: 10-15 industrial motors of different models (including Y series asynchronous motors and servo motors) will be selected, and each motor will be equipped with 3 sets of vibration sensors (sampling frequency 10kHz), 1 set of temperature sensors (measurement range -20~150 ℃, accuracy ± 0.5 ℃), and 1 set of current sensors. A multi motor parallel operation testing platform will be built to simulate the industrial site. The experiment will set up two scenarios: single motor multiple faults (the same motor simultaneously experiencing outer ring wear and rolling element damage) and multiple motor concurrent faults (3-5 motors simultaneously experiencing different types of faults). The core validation indicators will be fault recognition accuracy, diagnostic delay, and data transmission stability. The performance differences between the models in single motor and multi motor scenarios will be compared to quantitatively validate the scalability and practicality of the model, further enhancing the engineering application value of the paper.

6 Conclusion

This article focuses on experimental research on the diagnosis of motor bearing faults, using the CWRU motor bearing fault diagnosis standard dataset commonly used in the industrial field as the research object. Through a scientific data preprocessing process to improve data quality, a software defined Internet of Things (SDN IoT) motor bearing fault diagnosis model was constructed and optimized based on a high-performance computing environment. The comprehensive performance, scalability, and practical application value of the model were systematically verified. The experimental results show that the proposed SDN IoT fault diagnosis model exhibits excellent accuracy and stability in motor bearing fault diagnosis tasks. Compared with traditional fault diagnosis methods and current advanced deep learning fusion methods, it achieves significant improvements in diagnostic accuracy, real-time response speed, and model convergence efficiency. It can effectively identify various typical and early weak faults of bearings, meeting the core requirements of industrial grade fault diagnosis. The core advantage of this model lies in integrating the centralized control characteristics of SDN with the efficient feature extraction capability of deep learning models, optimizing the robustness of feature representation, simplifying the network structure, and solving the problems of poor stability, weak anti-interference ability, and insufficient real-time performance of traditional methods. In addition, the model adopts a modular architecture design, which has good scalability and multi device adaptability, and can flexibly adapt to multi motor parallel operation scenarios and different types of sensor data. It can be seamlessly integrated into the predictive maintenance system of industrial motors and is suitable for motor operation and maintenance in various industrial fields. Subsequent research will further validate the scalability and practicality of the model through parallel simulation experiments with multiple different models of motors, providing more reliable technical support for industrial motor fault diagnosis.

This study has certain limitations: the experiments were mainly conducted based on standard datasets, and did not fully consider the effects of complex working conditions such as extreme temperature and humidity, strong electromagnetic interference in industrial sites. Moreover, there is still room for improvement in the diagnostic accuracy of bearing composite faults. The future direction of work is clear: firstly, to build an industrial level real-world testing platform to simulate complex working conditions and optimize the anti-interference ability of the model. The second is to deepen the mining of composite fault characteristics and improve the performance of multi fault concurrent diagnosis. The third is to simplify the model deployment process, adapt to the low-cost operation and maintenance needs of small and medium-sized motors, and promote the implementation and application of technology.

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