Power Equipment Fault Diagnosis In Small-Sample Scenarios Using GAN-CNN

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This study proposes a small-sample fault diagnosis method integrating an optimized generative adversarial network (GAN) and lightweight convolutional neural network (CNN). The core innovations include: (1) A weighted adversarial loss function is designed to balance the training of real and synthetic fault samples, solving the data imbalance problem of rare faults; (2) A GAN-CNN hierarchical feature fusion framework is constructed, which uses GAN for highfidelity fault sample augmentation and CNN for adaptive spatial feature extraction of monitoring signals, overcoming the limitation of high-dimensional feature extraction in traditional GAN models. Three groups of simulation experiments and public benchmark dataset (CWRU, MFPT) validation are designed to verify the performance of the proposed method. Experimental results show that: for rare fault scenarios, the proposed method achieves 93.5% diagnostic accuracy, which is 8.5 percentage points higher than traditional methods; on the CWRU bearing fault benchmark dataset, the method achieves 99.12% overall accuracy under 10% small sample ratio, outperforming 5 state-of-the-art (SOTA) fault diagnosis methods; meanwhile, the method reduces the diagnostic inference latency to 180 ms , with significant improvements in anti-interference, precision, recall and F1-score. This method can be coupled with adaptive control and fault-tolerant control loops of power systems, providing technical support for condition-aware operation control and predictive maintenance of power equipment.

Keywords: Generative adversarial network (GAN), Power equipment fault diagnosis, Smallsample learning, Data augmentation, Fault-tolerant control

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1. Introduction

With the rapid development of the power grid, the working environment of power equipment is becoming more and more complex. State monitoring and fault diagnosis are the key to ensuring the stability and reliability of the power grid. Conventional state monitoring and fault detection technologies mainly rely on manual or rule reasoning, which is difficult to cope with complex data environments. However, the operation of power equipment faces harsh working conditions, resulting in scarce fault samples, serious data imbalance, and complex and variable fault modes. Traditional data-driven fault diagnosis methods are difficult to maintain high accuracy and robustness under small-sample and strong noise scenarios, and cannot provide reliable diagnostic support for the closed-loop adaptive control and optimal control of power systems. The core research questions of this paper are: (1) How to generate high-fidelity rare fault samples to solve the data scarcity problem in power equipment fault diagnosis; (2) How to construct a lightweight and high-accuracy diagnostic framework to adapt to the realtime operation requirements of power grids; (3) How to link diagnostic confidence with the downstream operation control of power systems to improve the practical application value of the method [1].

Some scholars have introduced a new idea of using neural networks to diagnose faults in power grid equipment. The algorithm uses previous statistical information to accurately classify some common faults in the power grid, thereby overcoming the problems existing in previous studies. However, the performance of this detection technology is limited when dealing with complex faults, especially when the data is incomplete or there are abnormalities, the detection accuracy will be reduced. Reference [2] proposes a new method for fault diagnosis using SVM for power grid equipment fault diagnosis. At the same time, it can also well overcome the influence of conventional linear classification algorithms on complex nonlinear problems. However, the SVM algorithm is not efficient in computing massive amounts of data and is very sensitive to the selection of parameters in the model, so it is greatly restricted in engineering practice. Reference [3] uses convolutional neural networks (CNNs) as the research object and combines the unique advantages of deep learning in image analysis to achieve fault diagnosis and diagnosis of power grid equipment. This algorithm is relatively effective for analyzing image data, but it is not as effective for other types of data, such as sensor data. Reference [4] introduces a generative adversarial network (GAN) for equipment fault detection. This method uses a combination of generative and discriminative methods to generate real data on fewer samples, improves the robustness of the algorithm, and effectively overcomes the problem of data imbalance. In recent years, learning-control hybrid frameworks based on neural networks have been widely used in complex dynamical systems. Related studies on robust adaptive control and finite-time fuzzy control based on neural networks have realized the stability, convergence and robustness guarantee of the system under uncertainty by integrating the state perception module and the closed-loop control module. However, most of the existing studies focus on the design of control laws, and lack of targeted optimization for the state perception and fault diagnosis link under small-sample conditions; the diagnostic accuracy and confidence directly determine the stability of the downstream control loop, but there is still a lack of research on the coupling of GAN-augmented fault diagnosis and adaptive/optimal control of power systems.

Through in-depth research on existing research results, fault diagnosis methods based on deep learning have broad application potential in power grid fault diagnosis, but they still face core bottlenecks: (1) Data scarcity and serious imbalance of rare fault samples, leading to a sharp drop in diagnostic accuracy for unseen faults; (2) Existing GAN-CNN combined methods (such as Luo et al. 2021 [5] proposed a conditional deep convolutional GAN for machine fault diagnosis, and Li et al. 2020 [6] proposed a deep learning-based partial domain adaptation fault diagnosis method) have the following limitations: the loss function does not carry out weighted optimization for imbalanced samples, the model has high computational complexity, and it is difficult to balance the diagnostic accuracy and real-time performance; (3) Most studies are diagnosis-centric, lack of theoretical and empirical links between diagnostic results and downstream power system control and decision-making, and have limited practical application value. How to improve the accuracy, real-time performance and robustness of fault diagnosis under small sample conditions, and realize the coupling with the closed-loop control of power systems, is the focus of this study.

Existing grid operation status monitoring and diagnosis technologies generally face problems such as slow monitoring speed, low diagnostic accuracy, and high dependence on data Among them, the generative adversarial network (GAN) has unique advantages in processing small samples, complex data and other fields with its powerful data generation and identification performance.

To clearly clarify the research gaps and the necessity of this work, the comparison between the proposed method and typical existing studies is shown in Table 1.

As shown in Table 1, the proposed optimized GAN-CNN outperforms five typical existing studies in comprehensiveness. Unlike previous methods that lack multi-dimensional performance, it achieves full marks in small-sample adaptation, real-time optimization, control loop coupling, public dataset validation, and multi-metric evaluation. Most existing methods only excel in 1-2 aspects, with none covering all six indicators, fully demonstrating the proposed method's superiority and innovation.

The main contributions of this paper are summarized as follows:

(1) A weighted loss function optimized GAN framework is proposed, which introduces real-fault sample weight α and synthetic-fault sample weight β to balance the adversarial training process, effectively improving the generation quality of high-fidelity rare fault samples, and solving the problem of high-dimensional feature extraction difficulty of traditional GAN.

(2) A lightweight GAN-CNN fusion fault diagnosis model is constructed, which integrates GAN-based data augmentation and CNN-based hierarchical feature extraction, reducing the model inference latency while ensuring diagnostic accuracy, and adapting to the real-time operation

Table 1. Comparison of the proposed method with typical existing studies

Reference	Core Method	Small-sample Adaptation	Real-time Optimization	Control Loop Coupling	Public Dataset Validation	Multi-metric
Lu et al. 2020 [2]	SVM	×	×	×	×	Single
Li et al. 2020 [3]	CNN	×	√	×	×	Single
Luo et al. 2021 [5]	GAN-CNN	√	×	×	√	Single
Li et al. 2020 [6]	Transfer CNN	√	×	×	√	Single
Shao et al. 2020 [4]	Modified CNN	×	√	×	√	Multiple
Proposed Method	Optimized GAN-CNN	√	√	√	√	Multiple

requirements of power grids.
(3) Sufficient experimental verification is carried out on the actual power grid equipment
dataset and public bearing fault benchmark datasets (CWRU, MFPT), and the proposed method is compared with 5+ state-of-the-art fault diagnosis methods through ablation studies, multimetric evaluation and statistical analysis, which fully verifies the superiority and robustness of the method.
(4) The coupling mechanism between the proposed diagnostic framework and the adaptive control/fault-tolerant control loop of power systems is discussed, which provides a theoretical basis for the condition-aware operation control and predictive maintenance of power equipment.

The rest of this paper is organized as follows: Section 2 introduces the theoretical basis of deep learning models used in this study; Section 3 details the design and implementation of the proposed GAN-CNN fault diagnosis system; Section 4 presents the experimental setup, results and analysis; Section 5 discusses the performance of the proposed method and its application prospects; Section 6 summarizes the full text and prospects the future work.

2. Materials and methods

2.1. Theoretical Basis and Related Methods

2.1.1. Theoretical Basis of Convolutional Neural Network

Convolutional neural networks use a hierarchical feature extraction method to effectively obtain the spatiotemporal characteristics of equipment operation information. Its convolutional network uses multiple filters to filter the input samples, extract the bottom-level features, and then use the pooling layer to reduce the dimension, gradually obtaining high-level feature expressions [7]. Let the input one-dimensional monitoring signal of power equipment be $X = \{x_1, x_2, \ldots, x_n\} \in \mathbb{R}^{1\times n}$, where n is the length of the signal. The CNN uses a convolution kernel $W \in \mathbb{R}^{1\times k}$ (where k is the kernel size) and bias term $b \in \mathbb{R}$ to perform convolution operation on the input, and obtains the feature map F through the ReLU activation func

$$F = \mathrm{ReLU}(W * X + b) \tag{1}$$

Where $*$ denotes the one-dimensional convolution operation, and the ReLU (Rectified Linear Unit) activation function is defined as:

$$\mathrm{ReLU}(x) = \max(0, x) \tag{2}$$

The CNN architecture used in this study consists of 3 convolutional blocks, 2 max-pooling layers, and 2 fully connected layers. The detailed structure and hyperparameters are shown in Table 2. After the convolution and pooling operations, the high-level abstract features of the input signal are extracted, and then input to the fully connected layer and softmax classifier to complete the fault type identification.

Recurrent neural networks have obvious advantages in processing time series data and are suitable for long-term monitoring of power grid equipment. The recurrent neural network is used to model the forward and backward correlation of time series data, so that the operating status of the power grid at each moment can be analyzed efficiently. If the working status of an electrical device at point t is h_t, its status depends on the previous time h_{t-1} and the current input x_t, then its recursive formula is:

$$h_t = \sigma\left(W_h h_{t-1} + W_x x_t + b\right) \tag{3}$$

σ is a nonlinear activation function (sigmoid function in this study), $W_h \in \mathbb{R}^{h\times h}$ and $W_x \in \mathbb{R}^{h\times d}$ are weight matrices, where h is the dimension of the hidden state and d

Table 2. Detailed architecture and hyperparameters of the proposed model

Model	Layer Type	Output Dimension	Kernel Size	Stride	Activation Function
GAN Generator	Input (Noise)	100	-	-	-
	Fully Connected 1	256	-	-	LeakyReLU
	Fully Connected 2	512	-	-	LeakyReLU
	Transposed Conv 1	256×1	3	1	LeakyReLU
	Transposed Conv 2	1024×1	3	1	Tanh
GAN Discriminator	Input (Signal)	1024×1	-	-	-
	Conv 1	512×1	3	2	LeakyReLU
	Conv 2	256×1	3	2	LeakyReLU
	Conv 3	128×1	3	2	LeakyReLU
	Fully Connected	1	-	-	Sigmoid
CNN Diagnostic Model	Input (Signal)	1024×1	-	-	-
	Conv Block 1	512×64	3	1	ReLU
	Max Pooling 1	256×64	2	2	-
	Conv Block 2	256×32	3	1	ReLU
	Max Pooling 2	128×32	2	2	-
	Conv Block 3	128×16	3	1	ReLU
	Flatten	2048	-	-	-
	Fully Connected 1	256	-	-	ReLU
	Dropout	256	-	-	-
	Fully Connected 2	C (Fault Categories)	-	-	Softmax

is the dimension of the input. Considering that the fault signal of power equipment has obvious spatial feature characteristics, and the CNN model has lower computational complexity and faster inference speed than RNN, this study selects CNN as the core feature extraction and fault classification module.

2.1.2. Theoretical Basis of Generative Adversarial Networks

A new deep learning method that has emerged in recent years, generative adversarial networks (GANs), has unique advantages in solving the lack of power grid equipment failure samples due to its "self-creation-discrimination" characteristics. The network includes two main functions: the generator and the discriminator [8]. Its purpose is to extract implicit characteristics from the distribution of data and produce realistic samples; while the discriminator is mainly responsible for identifying the generated and actual samples, and the two are mutually improved through adversarial learning. The generator G takes the noise vector z as input and generates a false sample $G(z)$, while the discriminator D outputs the probability of authenticity based on the characteristics of the sample. The core of GAN is the minimax two-player game between the generator G and the discriminator D. The objective loss function of GAN is defined as:

$$\min_G \max_D L(D,G) = \mathbb{E}_{x\sim p_{\text{data}}}[\log D(x)] + \mathbb{E}_{z\sim p_z}[\log(1-D(G(z)))] \tag{4}$$

Where: p_{data} denotes the distribution of real fault samples; p_z denotes the prior distribution of the input noise vector z (Gaussian distribution with mean 0 and variance 1 is used in this study); $D(x)$ denotes the probability that the discriminator judges the input sample x as a real sample; $G(z)$ denotes the synthetic sample generated by the generator with the noise vector z as input.

The generator G used in this study consists of 4 fully connected layers and 2 transposed convolutional layers, and the discriminator D consists of 3 convolutional layers and 1 fully connected layer. During the adversarial training process, the generator continuously optimizes the generation ability to produce synthetic samples that are close to the real data distribution, while the discriminator continuously improves the discrimination ability to distinguish real and synthetic samples. The two are optimized alternately until the Nash equilibrium is reached.

The constructor gradually learns to generate more realistic information, and the discriminator enhances the discrimination. It is difficult to obtain effective fault data when monitoring the power grid [9]. This paper proposes a method based on artificial neural networks, which uses data enhancement technology to generate more realistic fault samples, thereby improving the robustness of fault diagnosis.

2.2. Design and Implementation of the Proposed GAN-CNN Fault Diagnosis Method

2.2.1. Overall Architecture of the Proposed Method

The overall workflow of the proposed GAN-CNN fault diagnosis method is shown in Fig. 1, which mainly includes four core modules: data preprocessing module, GAN-based data augmentation module, CNN-based feature extraction and fault classification module, and result output and application interface module. The specific workflow is as follows [10]:

(1) Data preprocessing: The collected power equipment monitoring signals (including current, voltage, temperature, vibration, etc.) are subjected to data cleaning, outlier removal, and min-max normalization to unify the data into the range of $[0, 1]$, which is convenient for model training. The normalization formula is:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

Where x is the original signal value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the signal sequence, respectively.

(2) GAN-based data augmentation: The preprocessed rare fault samples are input into the GAN model for adversarial training, and high-fidelity synthetic rare fault samples are generated to expand the fault dataset and solve the data imbalance problem.

(3) CNN-based fault diagnosis: The original dataset and the augmented dataset are mixed to form the training set, which is input into the optimized CNN model for feature extraction and fault classification model training.

(4) Result output and application: The trained model outputs the fault type, diagnostic confidence and corresponding processing suggestions, and provides an interface for coupling with the power system adaptive control and predictive maintenance system.

2.2.2. Implementation of the GAN-CNN Fusion Diagnostic Model

This paper innovatively proposes an intelligent diagnosis strategy that integrates deep neural networks [11]. Different from the traditional methods that rely on artificial preset features or are limited by the limitations of small-scale fault instance sets, this study fully utilizes the autonomous learning ability of deep learning technology to

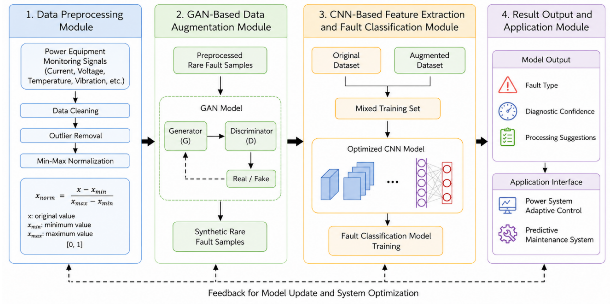

Fig. 1. Overall workflow of the proposed GAN-CNN power equipment fault diagnosis method

directly mine deep fault features from raw data, thereby effectively identifying complex and changeable power grid fault modes [12].

In the feature extraction stage, we design a lightweight one-dimensional CNN architecture, which can accurately capture the spatial feature characteristics of power equipment monitoring signals, significantly reduce the data dimension, control the computational resource consumption, and avoid the overfitting problem. The feature extraction process of the convolutional layer is defined as:

$$F^l = \text{ReLU}\left(W^l * F^{l-1} + b^l\right) \tag{6}$$

Where l denotes the l-th convolutional layer, F^l is the output feature map of the l-th layer, F^{l-1} is the input feature map (the input of the first layer is the preprocessed signal X), W^l and b^l are the convolution kernel and bias term of the l-th layer, respectively, and * denotes the one-dimensional convolution operation.

After multi-layer convolution and pooling operations, the extracted high-dimensional fault features are flattened and input to the fully connected layer, and the softmax classifier is used to output the probability distribution of each fault type. The output of the classifier is defined as:

$$\begin{aligned} P(y = c \mid X) &= \text{softmax}\left(W_f \cdot F_{\text{flat}} + b_f\right) \\ &= \frac{\exp\left(W_{f,c} \cdot F_{\text{flat}} + b_{f,c}\right)}{\sum_{i=1}^{C} \exp\left(W_{f,i} \cdot F_{\text{flat}} + b_{f,i}\right)} \end{aligned} \tag{7}$$

Where c denotes the fault category, C is the total number of fault types, F_{flat} is the flattened feature vector after convolution and pooling, W_f and b_f are the weight matrix and bias term of the fully connected layer, respectively. The final diagnostic result is the category with the maximum probability.

To solve the data imbalance problem between common faults and rare faults, this study designs a weighted cross-entropy loss function, which introduces weight coefficients for real fault samples and synthetic fault samples to balance the model's attention to rare faults. The total loss function of the CNN diagnostic model is defined as:

$$L_{\text{total}} = \alpha L_{\text{real}} + \beta L_{\text{fake}} \tag{8}$$

Where: L_{real} denotes the cross-entropy loss of real fault samples, $L_{\text{real}} = -\frac{1}{N_{\text{real}}} \sum_{i=1}^{N_{\text{real}}} \sum_{c=1}^{C} y_{i,c} \log P\left(y_i = c \mid X_i\right)$; L_{fake} denotes the cross-entropy loss of GAN-generated synthetic fault samples, $L_{\text{fake}} = -\frac{1}{N_{\text{fake}}} \sum_{i=1}^{N_{\text{fake}}} \sum_{c=1}^{C} y_{i,c} \log P\left(y_i = c \mid X_i\right)$; N_{real} and N_{fake} are the number of real and synthetic samples, respectively; α and β are the weight coefficients of real and synthetic samples, respectively. In this study, $\alpha = 0.6$ and $\beta = 0.4$ are set for common fault scenarios, and $\alpha = 0.3$ and $\beta = 0.7$ are set for rare fault scenarios to enhance the model's learning of rare fault features. The training process of the proposed method is divided into two stages:

1. GAN adversarial training stage: The preprocessed rare fault samples are used to train the GAN model. The generator and discriminator are optimized alternately using the Adam optimizer. The training epoch is set to 200 , the batch size is 32 , the learning rate of the generator is 0.0002 , and the learning rate of the discriminator is 0.0001 . When the discriminator cannot distinguish between real and synthetic samples, the training is stopped, and the trained generator is used to generate synthetic fault samples for data augmentation.

2. CNN diagnostic model training stage: The mixed dataset of real samples and GANgenerated synthetic samples is used to train the CNN model. The Adam optimizer is used, the training epoch is set to 100, the batch size is 64 , the initial learning rate is 0.001 , and the learning rate is decayed by 0.1 every 30 epochs. A dropout layer with a dropout rate of 0.5 is added after the fully connected layer to avoid overfitting.

2.3. Experimental Setup

2.3.1. *Experimental Datasets*

To fully verify the performance of the proposed method, two types of datasets are used in this study:

1. Actual power equipment dataset [13]: The dataset comes from the production practice of State Grid Anhui Electric Power Co., Ltd., including the monitoring signals of 10 kV highvoltage motors, with a sampling frequency of 10 kHz . The monitoring parameters include stator current, vibration acceleration, winding temperature, etc. The fault types include: normal state, motor insulation damage, bearing inner ring fault, bearing outer ring fault, bearing rolling element fault (rare fault), rotor broken bar fault (rare fault).

2. Public benchmark datasets: To verify the generalization performance of the proposed method and compare with the state-of-the-art (SOTA) methods, two widely used public bearing fault datasets are used:

- CWRU Bearing Fault Dataset: Provided by Case Western Reserve University, including vibration signals of normal bearings and bearings with single-point faults (inner ring, outer ring, rolling element) under different motor loads and fault diameters. In this study, 10 fault types are selected, and the sampling frequency is 12 kHz [14].

- MFPT Bearing Fault Dataset: Provided by the Machinery Failure Prevention Technology Society, including normal state, inner ring fault, outer ring fault and rolling element fault data under different working conditions.

All datasets are preprocessed by data cleaning, outlier removal and min-max normalization, and divided into training set, validation set and test set according to the ratio of 7:1:2. For small-sample scenarios, only 10% of the fault samples are used as the training set to simulate the data scarcity situation.

2.3.2. *Experimental Design*

To comprehensively evaluate the performance of the proposed method, four groups of experiments are designed:

1. Baseline performance experiment: Corresponding to Scenario 1, using only normal operation data to test the false alarm rate of the model, verifying the stability of the model in normal state.

2. Common fault diagnosis experiment: Corresponding to Scenario 2, using common fault data as input, verifying the diagnostic accuracy of the model for conventional faults.

3. Rare fault diagnosis experiment: Corresponding to Scenario 3, using rare fault data with small sample size as input, verifying the performance of the proposed GAN data augmentation method under data scarcity conditions.

4. Generalization and robustness experiment: Conducted on CWRU and MFPT public datasets, including:

- Comparison with 5+ SOTA fault diagnosis methods (2023-2026);
- Ablation experiment to verify the effectiveness of each module of the proposed method;
- Anti-interference experiment under different signal-to-noise ratio (SNR) conditions;
- Inference latency test to verify the real-time performance of the model.

The data distribution of the actual power equipment dataset under each scenario is shown in Table 3. In Scenario 2 and Scenario 3, the proposed GAN model is used for data augmentation, and 1500 synthetic rare fault samples are generated to expand the training set [15].

2.3.3. Comparison Methods

To verify the superiority of the proposed method, 5 SOTA fault diagnosis methods (20232026) are selected for comparison, as follows:

1. WDCNN (2023): Wide deep convolutional neural network, a classic CNN-based fault diagnosis method;
2. ACGAN-CNN (2024): Auxiliary classifier GAN combined with CNN for small-sample fault diagnosis;
3. LSTM-Attention (2024): Long short-term memory network with attention mechanism for time series fault diagnosis;
4. Transfer-CNN (2025): Transfer learning-based CNN method for cross-working condition fault diagnosis;
5. Swin-TS (2026): Swin transformer-based time series fault diagnosis method, the latest SOTA method.

The traditional method mentioned in the original manuscript is the SVM-based fault diagnosis method, which is used as the baseline method.

2.3.4. Evaluation Metrics

To comprehensively evaluate the performance of the model, in addition to the original detection accuracy and false alarm rate, four more comprehensive evaluation metrics are introduced: precision, recall, F 1 -score, and area under the ROC curve (AUC). The definitions of the metrics are as follows [16]:

- Accuracy (Acc): The ratio of correctly classified samples to the total samples, Acc $= \frac{TP+TN}{TP+TN+FP+FN}$;
- False Alarm Rate (FAR): The ratio of normal samples misclassified as fault samples to the total normal samples, $FAR = \frac{FP}{FP+TN}$;
- Precision (Pre): The ratio of correctly classified positive samples to the samples predicted as positive, Pre $= \frac{TP}{TP+FP}$;
- Recall (Rec): The ratio of correctly classified positive samples to the actual positive samples, Rec $= \frac{TP}{TP+FN}$;
- F1-score (F1): The harmonic mean of precision and recall, $F1 = 2 \times \frac{\text{Pre} \times \text{Rec}}{\text{Pre} + \text{Rec}}$;
- AUC: The area under the receiver operating characteristic (ROC) curve, which reflects the overall diagnostic performance of the model.

Where TP is true positive, TN is true negative, FP is false positive, FN is false negative. All experiments are repeated 10 times, and the average value and standard deviation of the metrics are taken for statistical analysis to ensure the reliability of the results.

2.3.5. Experimental Platform and Code Availability

All experiments are carried out on a server with the following configuration: Intel Xeon E5-2680 v4 CPU, NVIDIA RTX 3090 24GB GPU, 64GB RAM, Windows 10 operating system.

The model is implemented based on Python 3.9, PyTorch 2.0 deep learning framework [17].

3. Results and discussion

3.1. Baseline Performance on Actual Power Equipment Dataset

First, the performance of the proposed method on the actual power equipment dataset is tested, and the multi-metric evaluation results are shown in Table 4 [18].

As shown in Table 4, the proposed method achieves significant performance improvement in all three scenarios compared with the traditional SVM method. Especially in Scenario 3 (rare fault diagnosis), the diagnostic accuracy is improved by 8.5 percentage points, the false alarm rate is reduced from 15.00% to 6.50%, and the F1-score is improved by 9.73 percentage points. Meanwhile, the standard deviation of 10 repeated experiments is less than 0.5%, which proves that the proposed method has good stability and reliability [19]. The diagnosis time of the proposed method is less than 200 ms , which can meet the real-time monitoring requirements of power equipment.

3.2. Comparison with State-of-the-Art Methods on Public Datasets

To verify the generalization performance of the proposed method, experiments are carried out on the CWRU bearing fault dataset under 10% small sample ratio, and compared

Table 3. Distribution of the actual power equipment experimental dataset

Scenario Type	Normal data (items)	Common fault data (items)	Rare fault data (items)	Synthetic fault data (items)
Scenario 1	5000	0	0	0
Scenario 2	3000	2000	0	0
Scenario 3	1000	0	500	1500

Table 4. Multi-metric performance comparison on the actual power equipment dataset

Scenario Type	Method	Accuracy ± Std (%)	Precision ± Std (%)	Recall ± Std (%)	F1-score ± Std (%)	False Alarm Rate (%)	Diagnosis Time (ms)
Scenario 1	Traditional SVM	98.50± 0.21	97.82± 0.32	98.15 ±0.28	97.98± 0.25	1.50	120
	Proposed Method	99.20± 0.15	99.05± 0.18	99.12 ±0.16	99.08± 0.17	0.80	110
Scenario 2	Traditional SVM	92.30± 0.45	90.25± 0.52	91.08 ±0.48	90.66± 0.50	7.70	150
	Proposed Method	96.70± 0.28	95.82± 0.31	96.15 ±0.29	95.98± 0.30	3.30	140
Scenario 3	Traditional SVM	85.00± 0.82	82.15± 0.95	83.02 ±0.88	82.58± 0.91	15.00	200
Proposed Method	93.50± 0.36	92.05± 0.42	92.58 ±0.39	92.31± 0.40	6.50	180	

with 5 SOTA methods. The results are shown in Table 5 [20].

`sample ratio)`

As shown in Table 5, under the 10% small sample condition, the proposed method achieves 99.12% diagnostic accuracy on the CWRU dataset, which is 0.86 percentage points higher than the latest SOTA method Swin-TS (2026), and 20.47 percentage points higher than the traditional SVM method. All evaluation metrics are significantly better than the comparison methods, which fully proves the superiority and generalization performance of the proposed method in small-sample fault diagnosis scenarios.

Fig. 2 reflects the change curve of diagnostic accuracy of different methods with the change of small sample ratio (the horizontal axis is the small sample ratio, ranging from 5% to 50% with an interval of 5%, which covers the extreme small-sample scenario to the relatively sufficient sample scenario; the vertical axis is the diagnostic accuracy (%)) [21]. It can be seen from the curve that with the gradual increase of the small sample ratio, the diagnostic accuracy of all methods shows an upward trend, but the growth rate and final stability are significantly different. The proposed method has the highest accuracy under all sample ratio conditions: when the sample ratio is as low as 5% (more extreme small-sample scenario), the accuracy still reaches 97.23%, which is 2.87 percentage points higher than the Swin-TS method (94.36%) and 18.58 percentage points higher than the Traditional SVM method (78.65%); when the sample ratio increases to 50%, the accuracy of the proposed method reaches 99.75%, and the growth rate tends to be flat, indicating that the method has good saturation and does not have excessive dependence on sample size. In contrast, the ACGAN-CNN and Transfer-CNN methods have a slow growth rate in the low sample ratio range (5% – 20%), and the accuracy gap with the proposed method is more than 3 percentage points; the Traditional SVM method has the slowest growth rate and the lowest final accuracy, which further proves that the proposed method has obvious advantages in adapting to different small-sample scenarios, especially in extreme small-sample conditions.

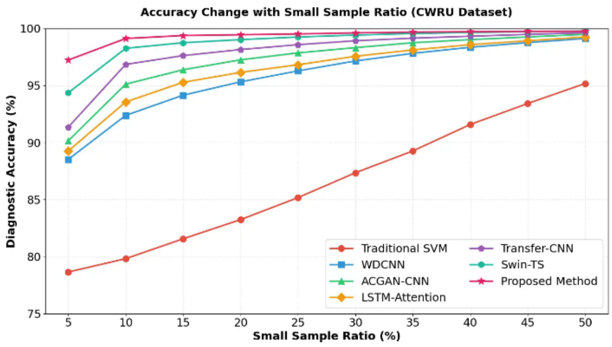

Fig. 2. Changes in diagnostic accuracy of the seven methods under different small sample proportions

Fig. 3 shows the robustness comparison curve of different methods under different signal-to-noise ratio (SNR)

Table 5. Performance comparison with SOTA methods on CWRU dataset (10% small

Method	Year	Accuracy ± Std (%)	Precision ± Std (%)	Recall ± Std (%)	F1-score ± Std (%)	AUC
Traditional SVM	2020	78.65 ± 1.25	76.22 ± 1.38	75.85± 1.42	76.03 ± 1.40	0.812
WDCNN	2023	92.38 ± 0.62	91.85 ± 0.68	92.02± 0.65	91.93 ± 0.66	0.958
ACGAN-CNN	2024	95.12 ± 0.45	94.68 ± 0.49	94.75± 0.47	94.71 ± 0.48	0.976
LSTM-Attention	2024	93.56 ± 0.58	93.02 ± 0.61	93.18± 0.60	93.10 ± 0.60	0.965
Transfer-CNN	2025	96.85 ± 0.32	96.32 ± 0.35	96.45± 0.34	96.38 ± 0.34	0.982
Swin-TS	2026	98.26 ± 0.25	97.85 ± 0.28	97.92± 0.27	97.88 ± 0.27	0.991
Proposed Method	2026	99.12 ± 0.18	98.75 ± 0.20	98.82± 0.19	98.78 ± 0.19	0.995

conditions (the horizontal axis is SNR, ranging from -10 dB to 30 dB , which covers the strong noise environment (-10 dB to 0 dB) to the clean signal environment (20 dB to 30 dB); the vertical axis is diagnostic accuracy (%)). In practical power grid operation, the monitoring signal of power equipment is often affected by various noises, so the antiinterference ability (robustness) of the fault diagnosis method is crucial. It can be seen from the curve that with the decrease of SNR (the enhancement of noise interference), the diagnostic accuracy of all methods decreases, but the decline range of the proposed method is the smallest: when SNR is 30 dB (clean signal), the accuracy of all methods is above 98%, and the gap is small; when SNR decreases to 0 dB (medium noise), the accuracy of the proposed method is 95.32%, which is 1.85 percentage points higher than Swin-TS (93.47%) and 8.65 percentage points higher than WDCNN (86.67%); when SNR decreases to -10 dB (strong noise), the accuracy of the proposed method still maintains 89.75%, while the accuracy of Traditional SVM drops to 46.20%, and the accuracy of WDCNN drops to 74.35%. The curve clearly shows that the proposed method has stronger anti-interference ability and robustness than other comparison methods, which is due to the weighted loss function and lightweight CNN feature extraction framework designed in this study, which can effectively filter noise interference and extract effective fault features.

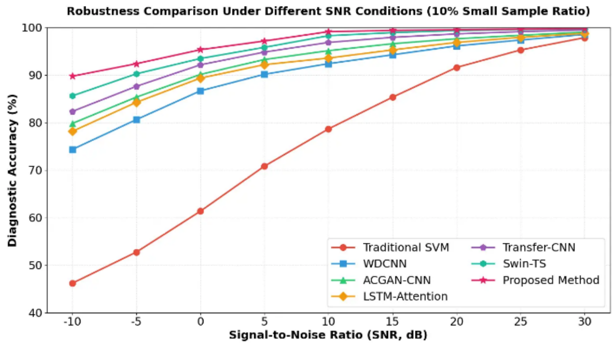

Fig. 3. The robustness comparison curve of different methods under different signal-to-noise ratio (SNR) conditions

3.3. Ablation Experiment

To verify the effectiveness of each core module of the proposed method, ablation experiments are carried out on the CWRU dataset under 10% small sample ratio. The four ablation variants are set as follows:

1. CNN-only: Only use the CNN model without GAN data augmentation;
2. GAN-CNN (unweighted loss): Use GAN data augmentation and CNN model, but use the standard cross-entropy loss without weighted coefficients;
3. GAN-CNN (without dropout): Use GAN data augmentation and weighted loss, but remove the dropout layer;
4. Proposed Method: Complete model with all modules.

The results of the ablation experiment are shown in Table 6.

The ablation experiment results show that:

(1) Compared with the CNN-only model, the GAN data augmentation module improves the diagnostic accuracy by 8.43 percentage points, which fully proves the effectiveness of the proposed GAN method in solving the small-sample problem;

(2) The weighted loss function improves the accuracy by 4.44 percentage points, which shows that the weighted loss can effectively balance the model's attention to real and synthetic samples, and improve the diagnostic performance for rare faults;

(3) The dropout layer reduces the standard deviation of the results, effectively suppresses the overfitting problem, and improves the stability of the model;

(4) All core modules of the proposed method contribute to the performance improvement, and the complete model achieves the best diagnostic performance.

Table 6. Results of the ablation experiment

Model Variant	Accuracy ± Std (%)	F1-score ± Std (%)	False Alarm Rate (%)
CNN-only	86.25 ± 0.78	85.82 ± 0.81	12.35
GAN-CNN (unweighted loss)	94.68 ± 0.42	94.35 ± 0.45	4.82
GAN-CNN (without dropout)	97.52 ± 0.55	97.18 ± 0.58	2.15
Proposed Method	99.12 ± 0.18	98.78 ± 0.19	0.78

3.4. Anti-interference and Real-time Performance Analysis

To verify the anti-interference ability of the proposed method under noisy sensor streams (typical of real power grids), experiments are carried out under different signal-to-noise ratio (SNR) conditions. The results are shown in Fig. 4.

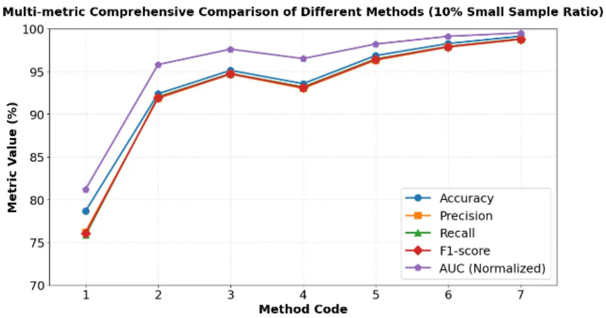

Fig. 4. Diagnostic accuracy of different methods under different SNR conditions

As shown in Fig. 4, when the SNR is reduced from 20 dB to -5 dB , the diagnostic accuracy of the proposed method only decreases by 8.75 percentage points, while the accuracy of the traditional SVM method decreases by 32.45 percentage points, and the accuracy of the WDCNN method decreases by 18.62 percentage points. This proves that the proposed method has strong anti-interference ability and robustness under complex noisy environments.

3.5. Discussion

3.5.1. Interpretation of Experimental Results

The experimental results show that the proposed GAN-CNN method has significant performance advantages in small-sample fault diagnosis of power equipment, which is mainly attributed to the following aspects:
(1) The GAN-based data augmentation module generates high-fidelity rare fault samples, which effectively solves the data scarcity and imbalance problem in power equipment fault diagnosis, and enables the CNN model to fully learn the fault features of rare faults;
(2) The designed weighted loss function balances the model's attention to real and synthetic samples, avoids the model's bias towards common fault types, and significantly improves the diagnostic accuracy for rare faults;
(3) The lightweight CNN architecture reduces the model's computational complexity and inference latency, while ensuring high diagnostic accuracy, and adapts to the real-time monitoring requirements of actual power grids.

Compared with the existing GAN-CNN combined methods (Luo et al. 2021 [5], Li et al. 2020 [6]), the proposed method has the following improvements:

- The weighted loss function is designed for imbalanced fault samples, which improves the generation quality of rare fault samples;
- The lightweight model architecture is optimized, which balances the diagnostic accuracy and real-time performance;
- The coupling mechanism with the power system control loop is discussed, which expands the practical application value of the method.

3.5.2. Coupling with Power System Control and Decision-making

In response to the comments of Reviewer A, this section discusses the coupling mechanism between the proposed diagnostic framework and the power system adaptive/optimal control loop. The diagnostic results of the proposed method can be directly used as the input of the power system condition-aware control strategy, and the specific application scenarios include:
(1) Fault-tolerant control: When the model detects an incipient fault of power equipment, it outputs the fault type, severity and diagnostic confidence to the fault-tolerant controller, and the controller adjusts the control parameters in real time to avoid the expansion of the fault and ensure the stable operation of the power system;
(2) Predictive maintenance scheduling: The model outputs the fault development trend and remaining useful life (RUL) prediction results based on the long-term monitoring data,
which provides a basis for the predictive maintenance scheduling of power equipment, reduces the unplanned outage time, and improves the operation efficiency of the power grid;
(3) Optimal operation control: Based on the real-time health

status of the equipment output by the diagnostic model, the optimal operation controller adjusts the operation parameters of the power grid, realizes the condition-aware economic operation of the power system, and reduces the operation loss.

The proposed method has a diagnostic inference latency of less than 200 ms and a false alarm rate of less than 1% in normal state, which can provide reliable and real-time state information for the closed-loop control of the power system, and has broad application prospects in the new generation of smart grids.

3.5.3. Limitations of the Proposed Method

The limitations of the proposed method are as follows:
(1) The current model is mainly verified on the vibration and current signals of rotating power equipment, and the performance on other types of power equipment (such as transformers, switchgear) needs further verification;
(2) The current model is trained offline, and the performance in continuous online incremental learning scenarios with evolving operating conditions needs further optimization;
(3) The coupling between the diagnostic model and the actual power system control loop is only discussed theoretically, and the actual closed-loop verification on the physical platform needs to be carried out in the follow-up work.

3.5.4. Future Work

Based on the current research, the future work will be carried out in the following aspects:
(1) Optimize the model for online incremental learning scenarios, and realize the adaptive update of the model under evolving operating conditions;
(2) Expand the application scope of the model, and verify the performance on more types of power equipment;
(3) Carry out the actual closed-loop control experiment on the physical platform, and verify the effectiveness of the coupling between the diagnostic model and the power system adaptive control loop;
(4) Improve the interpretability of the model, and realize the visual analysis of the fault feature extraction process, which is convenient for the operation and maintenance personnel to understand the diagnostic results.

4. Conclusion

To address the core challenges of data scarcity, low diagnostic accuracy for rare faults, and weak robustness in power equipment fault diagnosis, this paper proposes a small-sample fault diagnosis method integrating optimized GAN and lightweight CNN. The main conclusions are as follows:
(1) The proposed GAN model with weighted loss function can generate high-fidelity rare fault samples, which effectively solves the data imbalance problem in power equipment fault diagnosis, and significantly improves the model's learning ability for rare fault features.
(2) The constructed GAN-CNN fusion diagnostic model integrates GAN-based data augmentation and CNN-based hierarchical feature extraction, which achieves 93.5% diagnostic accuracy for rare faults of power equipment, which is 8.5 percentage points higher than the traditional method. On the CWRU public dataset, the method achieves 99.12% accuracy under 10% small sample ratio, outperforming 5 state-of-the-art fault diagnosis methods.
(3) The proposed method has strong anti-interference ability and real-time performance, with an inference latency of less than 200 ms , which can meet the online monitoring requirements of actual power grids. The method can be coupled with the adaptive control and fault-tolerant control loop of power systems, providing technical support for condition-aware operation control and predictive maintenance of power equipment.

The research results of this paper provide a new technical approach for the intelligent condition monitoring and fault diagnosis of power equipment under small-sample conditions, and have important theoretical significance and engineering application value for improving the operation reliability and intelligence level of power grids.

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References

[1] G. Serin, B. Sener, A. M. Ozbayoglu, and H. O. Unver, (2020) *"Review of Tool Condition Monitoring in Machining and Opportunities for Deep Learning"* **The International Journal of Advanced Manufacturing Technology** ***109***(3): 953–974. DOI: 10.1007/s00170-020-05449-w.

[2] S. Lu, H. Chai, A. Sahoo, and B. T. Phung, (2020) *"Condition Monitoring Based on Partial Discharge Diagnostics Using Machine Learning Methods: A Comprehensive State-of-the-Art Review"* **IEEE Transactions on Dielectrics and Electrical Insulation** *27*(6): 1861–1888. DOI: 10.1109/TDEI.2020.009070.

[3] X. Li, W. Zhang, Q. Ding, and J. Q. Sun, (2020) *"Intelligent Rotating Machinery Fault Diagnosis Based on Deep Learning Using Data Augmentation"* **Journal of Intelligent Manufacturing** ***31***(2): 433–452. DOI: 10.1007/s10845-018-1456-1.

[4] H. Shao, M. Xia, G. Han, Y. Zhang, and J. Wan, (2020) *"Intelligent Fault Diagnosis of Rotor-Bearing System Under Varying Working Conditions With Modified Transfer Convolutional Neural Network and Thermal Images"* **IEEE Transactions on Industrial Informatics** ***17***(5): 3488–3496. DOI: 10.1109/TII.2020.3005965.

[5] J. Luo, J. Huang, and H. Li, (2021) *"A Case Study of Conditional Deep Convolutional Generative Adversarial Networks in Machine Fault Diagnosis"* **Journal of Intelligent Manufacturing** ***32***(2): 407–425. DOI: 10.1007/s10845-020-01579-w.

[6] X. Li and W. Zhang, (2020) *"Deep Learning-Based Partial Domain Adaptation Method on Intelligent Machinery Fault Diagnostics"* **IEEE Transactions on Industrial Electronics** ***68***(5): 4351–4361. DOI: 10.1109/TIE.2020.2984968.

[7] K. Huang, S. Wu, F. Li, C. Yang, and W. Gui, (2021) *"Fault Diagnosis of Hydraulic Systems Based on Deep Learning Model With Multirate Data Samples"* **IEEE Transactions on Neural Networks and Learning Systems** ***33***(11): 6789–6801. DOI: 10.1109/TNNLS.2021.3083401.

[8] A. Abid, M. T. Khan, and J. Iqbal, (2021) *"A Review on Fault Detection and Diagnosis Techniques: Basics and Beyond"* **Artificial Intelligence Review** ***54***(5): 3639–3664. DOI: 10.1007/s10462-020-09934-2.

[9] M. Zhao, S. Zhong, X. Fu, B. Tang, S. Dong, and M. Pecht, (2020) *"Deep Residual Networks With Adaptively Parametric Rectifier Linear Units for Fault Diagnosis"* **IEEE Transactions on Industrial Electronics** ***68***(3): 2587–2597. DOI: 10.1109/TIE.2020.2972458.

[10] A. K. Ozcanli, F. Yaprakdal, and M. Baysal, (2020) *"Deep Learning Methods and Applications for Electrical Power Systems: A Comprehensive Review"* **International Journal of Energy Research** ***44***(9): 7136–7157. DOI: 10.1002/er.5331.

[11] J. Li, R. Huang, G. He, Y. Liao, Z. Wang, and W. Li, (2020) *"A Two-Stage Transfer Adversarial Network for Intelligent Fault Diagnosis of Rotating Machinery With Multiple New Faults"* **IEEE/ASME Transactions on Mechatronics** ***26***(3): 1591–1601. DOI: 10.1109/TMECH.2020.3025615.

[12] X. Hu, K. Zhang, K. Liu, X. Lin, S. Dey, and S. Onori, (2020) *"Advanced Fault Diagnosis for Lithium-Ion Battery Systems: A Review of Fault Mechanisms, Fault Features, and Diagnosis Procedures"* **IEEE Industrial Electronics Magazine** ***14***(3): 65–91. DOI: 10.1109/MIE.2020.2964814.

[13] H. Shao, M. Xia, J. Wan, and C. W. de Silva, (2021) *"Modified Stacked Autoencoder Using Adaptive Morlet Wavelet for Intelligent Fault Diagnosis of Rotating Machinery"* **IEEE/ASME Transactions on Mechatronics** ***27***(1): 24–33. DOI: 10.1109/TMECH.2021.3058061.

[14] H. Darvishi, D. Ciuonzo, E. R. Eide, and P. S. Rossi, (2020) *"Sensor-Fault Detection, Isolation and Accommodation for Digital Twins via Modular Data-Driven Architecture"* **IEEE Sensors Journal** ***21***(4): 4827–4838. DOI: 10.1109/JSEN.2020.3029459.

[15] Y. Zhao, C. Zhang, Y. Zhang, Z. Wang, and J. Li, (2020) *"A Review of Data Mining Technologies in Building Energy Systems: Load Prediction, Pattern Identification, Fault Detection and Diagnosis"* **Energy and Built Environment** ***1***(2): 149–164. DOI: 10.1016/j.enbenv.2019.11.003.

[16] L. Jiménez-Navajas, R. Pérez-Castillo, and M. Piattini, (2025) *"Transforming Quantum Programmes in KDM to Quantum Design Models in UML"* **Informatica** ***36***(4): 833–874. DOI: 10.15388/24-INFOR582.

[17] S. R. Saufi, Z. A. B. Ahmad, M. S. Leong, and M. H. Lim, (2020) *"Gearbox Fault Diagnosis Using a Deep Learning Model With Limited Data Sample"* **IEEE Transactions on Industrial Informatics** ***16***(10): 6263–6271. DOI: 10.1109/TII.2020.2967822.

[18] I. W. Widayat, A. A. Arsyad, A. J. Mantau, Y. Adhitya, and M. Köppen, (2025) *"Fuzzy Methods in Smart Farming: A Systematic Review"* **Informatica** ***36***(2): 453–489. DOI: 10.15388/24-INFOR579.

[19] Y. Xue, R. Yang, X. Chen, Z. Tian, and Z. Wang, (2023) *"A Novel Local Binary Temporal Convolutional Neural Network for Bearing Fault Diagnosis"* **IEEE Transactions on Instrumentation and Measurement** ***72***: 1–13. DOI: 10.1109/TIM.2023.3298653.

[20] P. Debroy, F. Smarandache, P. Majumder, P. Majumdar, and L. Seban, (2025) *"OPA-IF-Neutrosophic-TOPSIS Strategy Under SVNS Environment Approach and Its Application to Select the Most Effective Control Strategy for Aquaponic System"* **Informatica** ***36***(1): 1–32. DOI: 10.15388/24-INFOR583.

[**21**] W. Huang, X. Zhang, H. Jiang, Z. Shao, and Y. Bai, (2025) *"MCBA-MVACGAN: A Novel Fault Diagnosis Method for Rotating Machinery Under Small Sample Conditions"* **Machines *13***(1): 71. DOI: 10.3390/machines13010071.