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Enhancing Wind Farm Reliability: A Field of View Enhanced Convolutional Neural Network-Based Model for Fault Diagnosis and Prevention

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Abstract

Wind farms play a crucial role in renewable energy generation, but their reliability is often compromised by complex environmental and equipment conditions. This study proposes a field of view enhanced convolutional neural network (CNN) model for fault diagnosis and prevention in wind farms. The model is developed by collecting and processing wind farm fault data and compared with support vector machine (SVM) and k-nearest neighbor (KNN) models. The results showed that the proposed CNN model outperformed the other models in terms of convergence speed (17 iterations to reach the minimum loss), fault diagnosis accuracy (99.3% and 99.2% for inner and outer circle faults, respectively), and stable power output improvement. The model's application to maintenance scheduling and economic benefit analysis in a real wind farm case demonstrated its high consistency and accuracy in fault prediction and maintenance optimization. The proposed approach has the potential to enhance wind farm reliability, efficiency, and economy by enabling accurate fault diagnosis, early warning, and preventive maintenance.

Keywords: Enhanced visual field; Convolutional neural network; Wind farms; Fault diagnosis; Prevention model.

1 Introduction

Wind power, as a clean and renewable energy solution, has been rapidly expanding around the world, playing an increasingly important role in alleviating energy crisis and environmental change. With the continuous investment and optimization of renewable energy technologies, especially wind power technologies, the sustainability of wind power generation, the reduction of dependence on fossil fuels and the positive impact on the mitigation of global climate change have become hot issues in current research and practice [1, 2, 3]. However, wind farms often face complex environmental and technical challenges during operation, especially those related to equipment reliability and fault diagnosis [4, 5].

However, wind farms often face complex environmental and technical challenges during operation, especially those related to equipment reliability and fault diagnosis. Wind power generation is greatly affected by changing weather conditions, including wind speed, wind direction, and other meteorological factors. As a result, wind turbines in operation are more prone to failure due to these environmental factors. After a failure occurs, it not only reduces power generation and the wind farm's economic efficiency, but it can also cause severe equipment damage or shutdown. For example, studies have shown that the failure rate of wind turbines is as high as 25%, with gearbox, blade and generator failures being the most common. The economic losses caused by failures can reach millions of dollars annually, seriously affecting the economic efficiency and reliability of wind farms. In addition, the failure may also cause the equipment to shut down for a long time, further aggravating the loss [6, 7, 8]. Therefore, timely detection and prediction of potential failures of wind power equipment is crucial, which is a key link to ensure efficient and stable operation of wind farms. At present, the research status of wind farm fault detection mainly focuses on data analysis methods, model building methods, physical model methods, and intelligent monitoring systems. Tchertchian N et al. studied the optimal maintenance strategies for different offshore wind farms. A simulation model was implemented to achieve weather and fault analysis as well as operation and maintenance, demonstrating how different maintenance strategies affect the environmental performance of a wind farm [9]. Mengfei Q et al. used the SIMORiflex-Aerodyn code to conduct a full coupling analysis of 10 MW large single-pile offshore wind turbines and studied the response characteristics of offshore wind turbines in different typhoon areas. The results showed that, under the shutdown condition of high wind speed, aerodynamic load played an important role in large single-pile wind turbines [10]. Anderson F et al. designed a Bayesian data modeling method for evaluating the operational efficiency of offshore wind farms. This method studied the effect of the shift pattern of technicians, especially the night shift corrective maintenance strategy applied in the field throughout the winter. It was found that the time-based technology availability increased by approximately 0.64% per year in specific locations [11]. Congshan L et al. proposed a coordinated control strategy based on frequency division. They used a low-pass filter to distinguish between high-frequency and low-frequency power fluctuations. Results showed that the frequency division control of the wind farm was coordinated with that of the flexible DC system. This effectively reduced the frequency fluctuation of the main grid caused by the AC system faults and improved the stable operation capability of AC and DC systems [12]. Jin X et al. proposed a wind farm power coordination control strategy to improve the reactive power support capability of the power grid under over-voltage. Studies showed that the proposed control strategy effectively suppressed the over-voltage of the outgoing AC network and improved the transmission capacity of the system [1].

Although existing research provides a basis for fault diagnosis and prevention in wind farms, most methods have limitations in dealing with complex environmental variables and unknown fault modes. In addition, these studies often ignore the comprehensive utilization of multi-source data of wind turbines, which limits the accuracy and efficiency of fault prediction. Therefore, it is particularly urgent to explore a method that can comprehensively analyze multi-source data and improve the accuracy of fault diagnosis.

A successful wind farm fault diagnosis and prevention system must enable fast and reliable anomaly monitoring and trend prediction to minimize economic losses and safety risks caused by failures. In this regard, the Convolutional Neural Network (CNN), as a powerful image and sequence data analysis tool, has shown excellent performance in feature extraction and pattern recognition. More attention has been given to designing a data-driven model that combines historical fault data and real-time monitoring data to achieve more accurate fault warnings. Shilin S et al. proposed a deep neural network method to measure spatial and temporal features in the medium and built a coarse learner and multiple fine learners to solve the problem of data imbalance. Experimental results showed that on two datasets, the proposed method outperformed the four benchmark methods [13]. Wenliao D et al. developed a combined 1D and 2D CNN for fault diagnosis of rotating machinery. The experimental results showed that bearings and gears had excellent classification performance under different working conditions. The average diagnostic accuracy of ten runs on the Case Western Reserve University bearing dataset was 99.92%, and the variance was 3.96e-6. The average diagnostic accuracy of ten runs on the worm gear data set was 99.82% and the variance was 7.82e-6 [14]. Zhijie X et al. proposed a fault diagnosis method for ball screws based on continuous wavelet transform and a two-dimensional CNN. The diagnosis results of different types of faults showed that the average recognition rate of the proposed fault diagnosis method reached 99.67% [15]. Jian C et al. proposed a machine fault diagnosis method using deep transmission CNNs and extreme learning machines. Experimental results showed that the proposed method greatly reduced the calculation time of the model, while ensuring high diagnostic accuracy, and the performance of this method was superior to other state-of-the-art methods [16]. Hongpeng L proposed a fault signal recognition method based on external correction and periodic correction of mechanical equipment fault features to extract the signal features of equipment faults. Experimental results showed that the proposed method effectively improved the fault diagnosis capability of mechanical equipment and the safety of equipment operation, showing strong generalization ability [17]. Qizi et al. proposed an intelligent fault diagnosis method for rolling bearings based on short-time Fourier transform and CNNs. The results showed that the proposed method was superior to other comparison methods, achieving 100% and 99.96% recognition accuracy on the Case Western Reserve University and Machine Fault Prevention Technology Association data sets, respectively [18]. Mohammadreza G proposed a novel deep subdomain adaptive graph CNN. The experimental results showed that combining the structured subdomain with the domain adaptation method was of great significance in obtaining an accurate data-driven model [19].

In general, in the field of wind power, fault diagnosis methods are essential to ensure operational efficiency and economic efficiency. However, existing fault diagnosis techniques often have some limitations, such as insufficient diagnostic accuracy, high maintenance costs and slow response to complex fault types. In the face of these challenges, a fault diagnosis and maintenance strategy based on REFCNN model is proposed to optimize the maintenance plan of wind farms through more accurate fault prediction and economic benefit analysis. The innovation of this approach lies in its ability to consider the impact of fault types on wind farm operations, as well as the specific contribution of maintenance activities to economic benefits, enabling more efficient and economical maintenance decisions. Research objectives include verifying the effectiveness of REFCNN model in fault diagnosis accuracy and maintenance scheduling efficiency, and exploring the impact of different fault types on the economic benefits of wind farms. The aim of these research contributions is to promote sustainable and efficient wind farm management, thereby contributing to the overall progress in the field of renewable energy.

2 Research method

2.1 Fault Feature Recognition Design for Wind Farm

The dynamic operating conditions of wind power gearboxes often result in time-varying fault signals, where the frequency and amplitude of fault features change over time. However, the fault feature frequency of the rolling axis remains stable despite environmental variations, making it a reliable recognition feature for wind farm faults. The failure frequency of the rolling shaft inner ring is mathematically represented as formula (1).

$$f_i = \frac{n}{2}(1 + \frac{d}{D}\cos\phi) \times f_r \tag{1}$$

In formula (1), D represents the pitch diameter of the rolling bearing. d represents the diameter of the rolling element. n represents the number of rolling elements. ϕ represents the contact angle. f_r represents the rotational frequency of the shaft on which the bearing is located. The failure of the inner ring of the rolling shaft denotes the occurrence of failure or damage within this specific component. The failure frequency of the outer ring of the rolling shaft can be expressed by formula (2).

$$f_o = \frac{n}{2}(1 - \frac{d}{D}\cos\phi) \times f_r \tag{2}$$

The failure of the outer ring of the rolling shaft refers to damage or malfunction within this component. It works together with the inner ring and rolling elements to support and guide the bearing's operation. The failure frequency of the rolling element of the rolling shaft can be represented by formula (3).

$$f_b = \frac{D}{2d}(1 - (\frac{d}{D})^2\cos^2\phi) \times f_r \tag{3}$$

The occurrence of failure or damage to components such as balls or rollers within the rolling bearing is indicated by the failure of the rolling element in the rolling shaft. The rolling element is responsible for supporting and transmitting loads within the bearing system. The failure frequency of the rolling shaft holder can be depicted using formula (4).

$$f_c = \frac{1}{2}(1 - \frac{d}{D}\cos\phi) \times f_r \tag{4}$$

The failure of the cage in the rolling shaft indicates the occurrence of failure or damage to the cage component within the rolling bearing. The cage plays a crucial role in maintaining the proper spacing and positioning of the rolling elements. In terms of sample data, the recognition frequency output of a single neuron can be represented by formula (5).

$$y = f(\sum_{i=1}^{n}(w_i x_i + b)) \tag{5}$$

In formula (5), y represents the neuron output. w_i represents the weights corresponding to each input. b represents bias. f represents activation function. x_i represents sample data frequency. Formula (1) defines the extraction process of fault features, and formula (2) strengthens the identification ability of fault signals through mathematical transformation. Formulas (3) to (5) are used to classify and evaluate fault characteristics. This allows the model to effectively distinguish between different types of faults and assess their potential impact on wind farm operation.

Shallow neural networks are used for classification and recognition of sample frequencies, as shown in Figure 1.

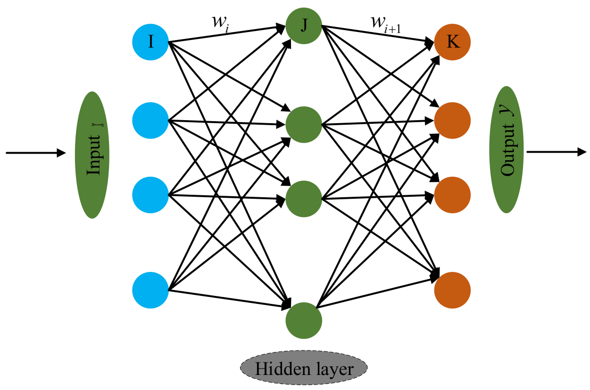


Figure 1: Schematic diagram of shallow neural network recognition for sample frequency

In Figure 1, a typical neural network includes input, hidden, and output layers. The input layer receives data, while the hidden layer performs calculations and feature extraction. By using neurons and activation functions, the output layer generates frequency recognition results. The network learns the relationship between sample frequency and labels through training and backpropagation, updates weights and biases, and improves frequency recognition accuracy. To improve the weight values, reuse rate, and fully utilize the local features of the image, a two-dimensional convolution operation is adopted, as shown in formula (6).

$$X_j^n = f(\sum_{i=1}^{m} X_i^{n-1} K_{ij}^n + b_j^n) \tag{6}$$

In formula (6), X_j^n is the $j-th$ feature graph of layer n . X_i^{n-1} is the $i-th$ feature graph of the previous layer of layer n of the network. Convolution kernel K_{ij}^n is used for the convolution operation between feature graph X_j^n and feature graph X_i^{n-1} . m represents the number of feature graphs to be convolved. b_j^n represents the bias term of the $j-th$ feature graph of layer n . Activation function f is used to activate feature graph. Among them, the feature map is pooled by the block division of 2×2 . The schematic diagram of the two-dimensional convolution operation is shown in Figure 2.

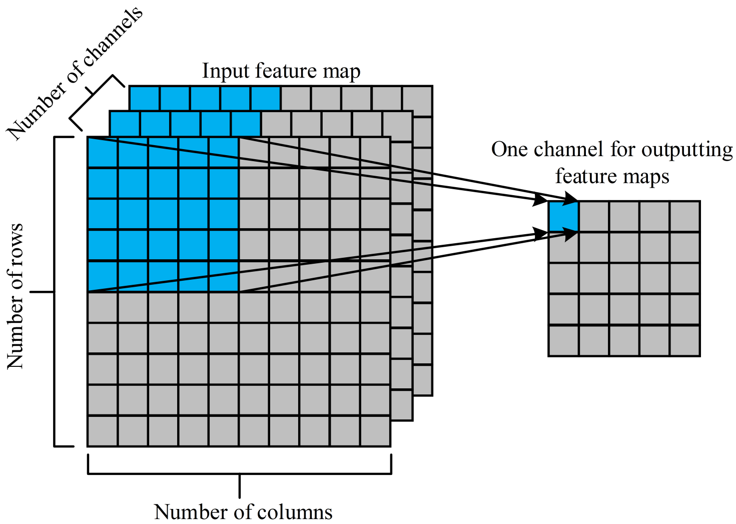


Figure 2: Schematic diagram of two-dimensional convolution operation

Figure 2 illustrates the process of two-dimensional convolution, where the convolution kernel scans from the top left corner and performs element-wise multiplication and addition with the input image's nine-grid to generate the output value. This convolutional layer effectively reduces the number of parameters while maintaining the same size of the feature map as the input, resulting in a large parameter count. To address this issue, the pooling layer is introduced to reduce the number of parameters by shrinking the feature map's size and capturing aggregated statistics within specific regions. The pooling operation is mathematically represented by formula (7).

$$X_j^n = f(down(X_j^{n-1})) \tag{7}$$

In formula (7), *down* is the sampling function. To solve the problem of excessive parameters and high dimensionality of feature maps in traditional CNNs, all feature maps of the previous layer are directly connected to the input of the current layer, as shown in Figure 3.

In Figure 3. a visual enhancement neural network utilizes a neural network model to eliminate noise from images, leading to improved image quality and recognition capabilities. This network maps noisy images to the original image, undergoes multiple feature extraction processes, and ultimately produces a clear feature image as the output. However, as the number of network layers increases, the issue of reduced model training efficiency becomes more pronounced. To address the challenge of decreased training efficiency, formula (8) employs the softmax function.

$$y_i = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} \tag{8}$$

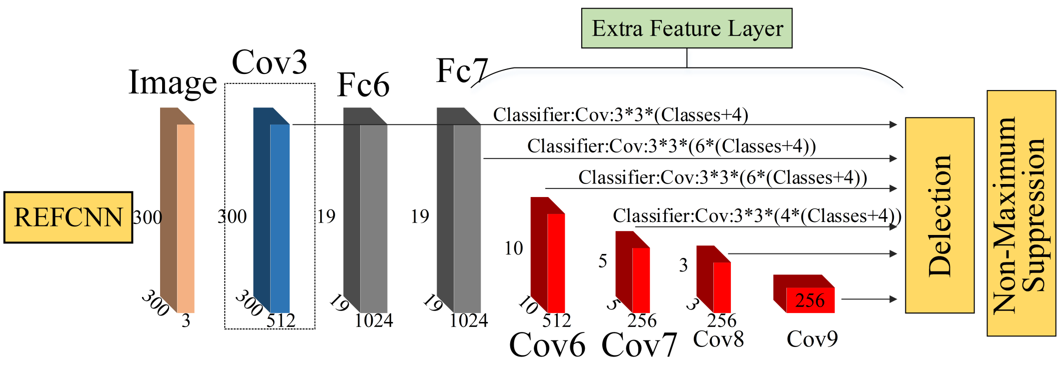


Figure 3: Schematic diagram of visual enhancement neural network

In formula (8), N represents the number of different categories involved in the classification task. Each category x_i, $y_i(i = 1, 2, ..., N)$ has corresponding feature representations in the output layer, which are transformed into real values after $softmax$ function mapping. Therefore, the frequency characteristics of wind turbine are extracted by Fourier transform. Then, CNN is used to analyze and identify these features.

2.2 Fault Identification and Classification Method Construction for Wind Farm

The monitoring equipment and remote-control system enable real-time monitoring of the wind farm status and remote equipment control. The regulatory structure for wind farm failures is shown in Figure 4.

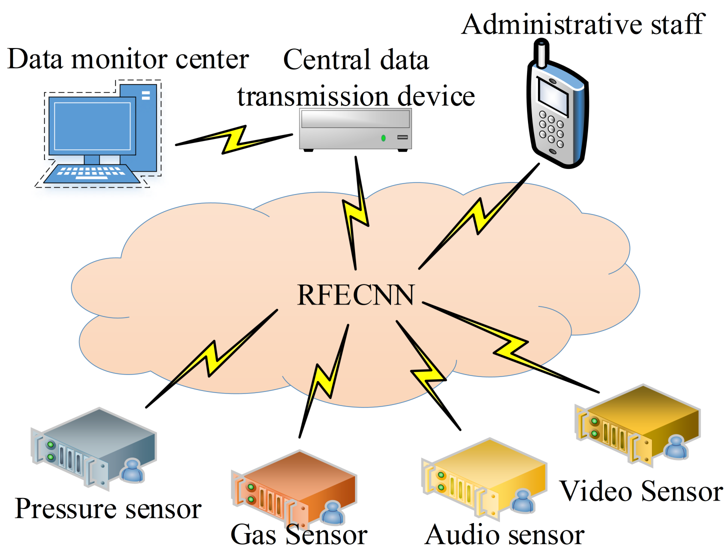


Figure 4: Wind farm fault supervision structure

In Figure 4, through the remote-control system, monitoring data of the fan can be received promptly, and faults can be analyzed and warned. At the same time, the remote-control system can also remotely operate and adjust the fan. To effectively capture fault information, short-term features between adjacent points of vibration signals are aggregated to extract more global fault features, as shown in formula (9).

$$z_i^j = f(w_j^T x_{ij+N-1} + b_j) \tag{9}$$

In formula (9), w_j represents the filter, which is responsible for filtering the input data and obtaining the activation value of $i - th$ point. The two-dimensional convolution can increase the view receptive field of the convolution kernel, and the void convolution in two-dimensional space is shown in formula (10).

$$(F_{*_r} k)(p) = \sum_{s+rt} F(s)k(t) \tag{10}$$

In formula (10), $*_r$ represents void convolution and p represents the receptive field size of void convolution. F is a two-dimensional input feature map and s is its definition domain. k represents a convolutional kernel and t is its domain of definition. The classification of output features requires assigning different weights to individual learners to adjust their contribution to the overall model, as shown in formula (11).

$$H(x) = C_{argmax} \sum_{i=1}^{M} w_i h_i^j(x) \tag{11}$$

In formula (11), the weight w_i of h_i is usually greater than or equal to 0, and the value range is $1-M$, where M is the sum of the total weight. h_i^j can be divided into "hard voting" and "soft voting" according to the value range. Through reasonable weight allocation, key features can obtain greater weights, thus occupying an important position in the final prediction results. The process of fault classification and identification is shown in Figure 5.

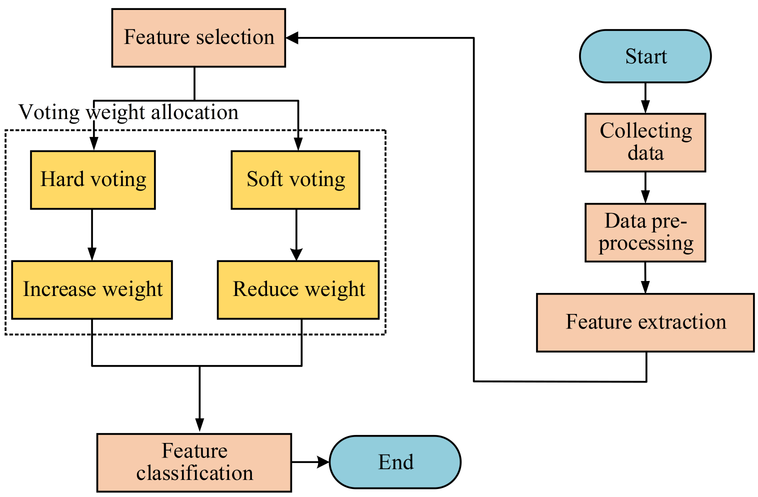


Figure 5: Fault classification and identification process

In Figure 5, first, multi-category fault data samples are collected, and preprocessing and feature extraction are conducted. Subsequently, weighted voting is performed on the extracted features to enhance the weight of important features and reduce the weight of secondary features. Finally, the results are classified and output. After dynamic weighting layer, the output of the model is shown in formula (12).

$$P_k = \sum_{i=1}^{n} w_i p_{i,k} \tag{12}$$

In formula (12), P_k represents the probability that the vibration data belongs to k class after model processing. Due to the range of probability values between 0 and 1, normalization is performed on P_k . Next, the cross-entropy loss is updated as shown in formula (13).

$$P_k = P_k / \sum_{k=1}^{K} P_k \tag{13}$$

The parameters of the model are updated using the cross-entropy loss function using formula (13), where the weight w_i is also continuously updated during the network training process. According to the gradient descent method, the update of weights is shown in formula (14).

$$w_i - \eta \frac{\partial L}{\partial w_i} \longrightarrow w_i \tag{14}$$

In formula (14), the learning rate is η . Due to the non-negative weight w_i of the model, a threshold has been set to ensure that w_i is always updated. After completing fault diagnosis, different faults are classified by labels, and the objective function of model training is shown in formula (15).

$$Loss = L_c + L_{mmd} = -\sum_{j=1}^{N_{class}} y_j \log_{y_j} + \sum_{i=1}^{m} \alpha_i MMD_i(F_i^l, F_i^u) \tag{15}$$

In formula (15), y_i represents the true label of the sample and y_j represents the prediction probability output by the neural network. α_i represents the penalty factor for the difference in edge probability distribution between labeled and unlabeled samples in the i fully connected layer. F_i^l represents the output feature values of labeled and unlabeled samples at different layers, representing the expression of features. In general, the fault identification and classification method adopts a composite strategy that integrates short-term feature aggregation, void convolution and weighted voting to improve the accuracy and efficiency of fault detection. Short-term feature aggregation extracts valuable information from time series data. To enhance the model's ability to identify fault features, hollow convolution is applied to expand the sensitivity field of features. The weighted voting mechanism comprehensively considers the recognition results of different features and models, and improves the accuracy and robustness of fault classification through weight allocation.

The experiment uses Gearbox Fault Data from the National Renewable Energy Laboratory (NREL), which contains vibration and sound signal data for different wind turbine failure states. The system configuration parameters of the trained neural network are shown in Table 1.

Table 1: System configuration parameters for training neural networks

Parameter	Description	Values
Learning Rate	Controls the step size of parameter updates	0.1
Batch Size	Number of samples used in each training iteration	32
Number of Epochs	Total training iterations	100
Activation Function	Non-linear function for introducing non-linearity	Sigmoid
Optimizer	Optimization algorithm for updating model parameters	SGD
Loss Function	Measures the difference between predictions and labels	MSE
Regularization	Techniques to prevent overfitting	Dropout
Learning Rate Scheduling	Dynamic adjustment of learning rate	Learning Rate Decay
Weight Initialization	Methods for initializing model weights	Random

In the analysis of applying the model to the operation, maintenance, and management of wind farms, a coastal wind farm is selected as the experimental subject. This wind farm demonstrates stable electricity generation and utilizes modern wind power generation technology. To provide context for the experiment, Table 2 shows key equipment parameters of the wind farm.

Table 2: Some key equipment parameters of wind farms

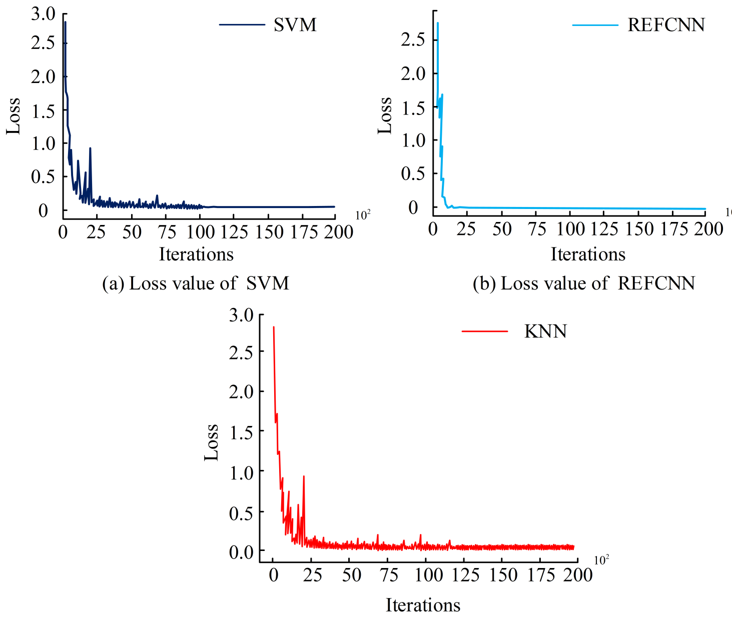
Parameter	Description
Turbine Model	ABC-6000
Turbine Capacity	6 MW
Tower Height	90 meters
Blade Diameter	140 meters
Cut-In Wind Speed	3.5 m/s
Cut-Out Wind Speed	30 m/s
Wind Speed Curve	[0-3.5 m/s]: 0%, [3.5-5 m/s]: 10%, [5-7 m/s]
Generator Type	Asynchronous Generator
Grid Connection Type	Substation Connection
Transformer Capacity	7 MVA
Substation Voltage Level	66 kV

The application of the model in wind farm operation and management encompasses various aspects, necessitating a comprehensive consideration of all needs to achieve optimal benefits. Key factors in the application of the model include maintenance scheduling and economic benefit analysis. Maintenance scheduling involves planning and coordinating regular maintenance and repair tasks for wind power equipment within the wind farm's operation and management. In the experimental setting, parameters are set based on environmental factors such as wind speed, temperature, and the operating state of the wind turbine. The model's robustness and adaptability are tested by closely simulating actual operating conditions. The selection of wind farm parameters is more focused on reflecting typical wind farm operation characteristics, so as to simulate the real wind farm environment and ensure the practicability and popularization of the research results. In summary, the selection of these specific settings is not only based on simulating the actual operating environment of wind farms, but also to verify the practical application effect of the model and ensure the reliability and effectiveness of the research results.

3 Result and discussion

3.1 Performance Evaluation of Fault Diagnosis and Prevention Models

To verify the effectiveness of the RFECNN model, it was first compared with a Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) on the same dataset to verify the model's effectiveness. After randomly selecting training and testing samples, the loss values of different algorithms are shown in Figure 6.



(a) Loss value of SVM (b) Loss value of REFCNN (c) Loss value of KNN

Figure 6: Loss for different algorithms

In Figure 6, SVM reached the minimum loss value after 100 iterations, and the loss curve fluctuated less in the first 100 iterations, demonstrating relatively stable convergence. After 17 iterations, REFCNN reached the minimum loss value, indicating a fast training speed and a very smooth loss curve. This indicated that the convergence process of the model was very stable and was not affected by noise or instability. In contrast, the KNN algorithm only reached the minimum loss value after 125 iterations, and the loss curve fluctuated greatly. This was because KNN was an inert learning algorithm that heavily relied on training data and might be affected by small changes in training data in different iterations. The recognition accuracy of different algorithms for four types of faults is shown in Figure 7.

In Figure 7, there were differences in the recognition performance of different machine learning algorithms. The KNN algorithm exhibited relatively low average accuracy, with 85.3%, 86.2%, 86.7%, and 86.9%, respectively. The SVM algorithm demonstrated higher average accuracy, with 91.4%, 91.1%, 91.7%, and 90.8%, respectively. Compared to this, the REFCNN algorithm exhibited outstanding performance in identifying inner circle faults and outer circle faults, reaching 99.3% and

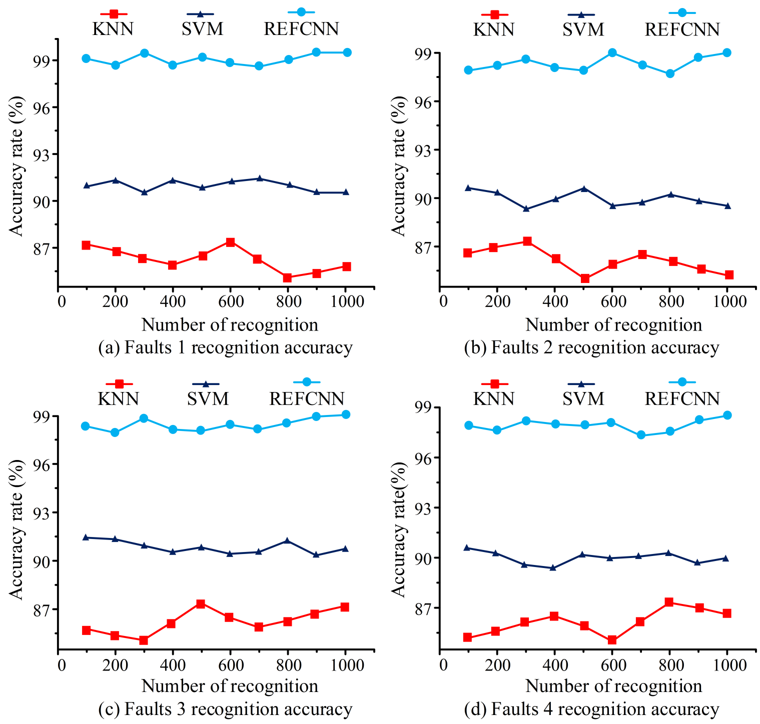


Figure 7: Recognition accuracy of different algorithms for four faults

99.2% respectively. However, the performance of REFCNN was relatively poor in rolling element faults and cage faults, with accuracy rates of 86.7% and 86.9%, respectively. These results reflected the advantages and disadvantages of different algorithms in dealing with different fault types. KNN exhibited relatively low accuracy, SVM exhibited balanced performance among different fault types, and REFCNN exhibited outstanding accuracy in identifying inner and outer circle faults. RFECNN model outperformed SVM and KNN in convergence speed and fault recognition accuracy. Compared to other advanced methods, RFECNN showed better performance through detailed feature processing and fast learning mechanism. This advantage was due to its ability to accurately capture changes in fault signals, as well as the accelerated convergence speed of end-to-end training. The results of the stable output power of wind farms using different algorithms for fault prevention at different times are shown in Figure 8.

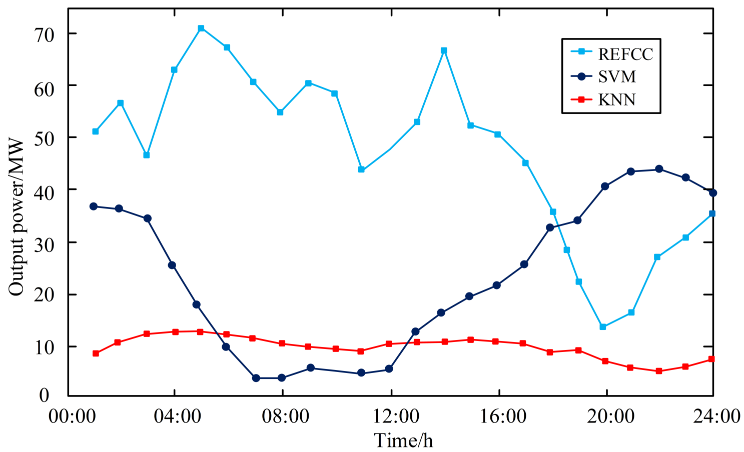


Figure 8: Stabilized power output results for wind farms at different moments

From Figure 8, under the fault prevention strategy of wind farms, different algorithms had significantly different impacts on the stable output power of wind farms. The REFCNN algorithm exhibited the best performance, reaching the highest stable output power of 72.1MW at 05:34, with an average stable output power of 51.9MW. The SVM algorithm took second place, reaching the highest stable output power of 43.4MW at 22:14, with an average stable output power of 23.9MW. The KNN algorithm performed the worst, reaching the highest stable output power of 14.8MW at 03:54, with an average stable output power of 9.8MW. The RFECNN model could efficiently convert fault diagnosis results into preventive measures. It could identify potential fault signals in real-time and trigger corresponding preventive strategies, such as adjusting operational parameters or initiating maintenance procedures to avoid faults. Furthermore, the model improved the self-protection capabilities of wind farms against potential faults by implementing real-time monitoring and an automatic response mechanism. This highlighted the benefits of integrating fault diagnosis and prevention.

3.2 Wind Farm Model in Operation and Management

The predicted and actual scores of the REFCNN model for maintenance scheduling of a certain wind farm are shown in Figure 9.

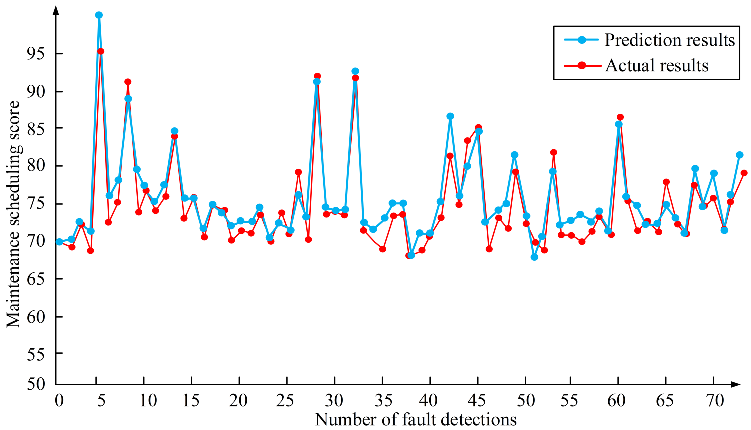


Figure 9: Score for maintenance and scheduling of wind farm faults

In Figure 9, the REFCNN consistency and accuracy in predicting the fault maintenance scheduling performance of a certain wind farm were remarkable. By comparing the predicted scores of the model with the actual score curve, it was evident that there was a high degree of agreement between them. It was worth pointing out that regardless of the number of fault detection points, the REFCNN model always provided relatively accurate maintenance scheduling prediction scores. When increasing the number of fault detection points from 5 to 70, the average score predicted by the model remained relatively stable, with an average score of 74. The actual maintenance scheduling score also showed a similar trend with the increase of fault detection points, with an average score of 73. The comparison between different fault prediction maintenance weights and the economic benefits of wind farms is shown in Figure 10.

Figure 10 clearly revealed the significant differences in predictive maintenance weights and economic benefit rates under different fault types. In the case of inner circle failure, the model assigned a relatively high maintenance weight (0.29), which implied its importance in maintenance scheduling and was consistent with a correspondingly high predicted economic benefit rate (0.853). The concern of the value was that even in this case, the actual economic benefit rate remained at a good level (0.756). For the outer ring failure, although its maintenance weight was relatively low (0.16), the predicted economic benefit rate was 0.435, which was close to the actual benefit rate (0.441). The main challenges of applying the prediction of RFECNN model to the actual decision-making process included the accuracy of data, real-time performance and the feasibility of maintenance strategy. The prediction results of the model should be closely combined with the actual operation of the wind farm to ensure the timeliness and effectiveness of the decision. When implementing the maintenance plan recommended by the model, the operational strategy of the wind farm, the allocation of maintenance resources, and the possible economic impact should be considered. For example, projected maintenance times needed to be coordinated with the wind farm's generation plan and grid demand

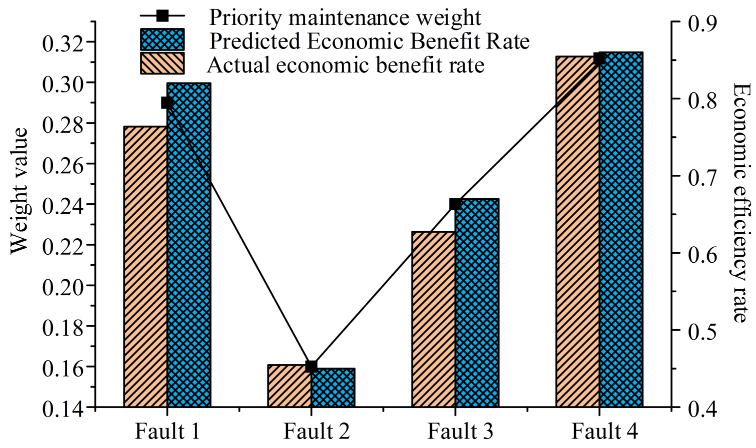


Figure 10: Economic efficiency of wind farms with different priority maintenance weights for faults

to reduce the impact of downtime on power supply. By comprehensively considering these factors, the application of RFECNN model could provide more scientific and reasonable maintenance decision support for wind farms, so as to achieve fault prevention and maximize economic benefits.

3.3 Discussion

In this study, the field-enhanced CNN model can effectively improve the fault diagnosis and prevention ability of wind farms, and it is expected that this model is better than traditional machine learning methods in diagnosis accuracy and processing speed [20]. The research results support this hypothesis. RFECNN converges quickly when the number of iterations is small, and demonstrates superior accuracy and remarkable prediction consistency in practical wind farm fault diagnosis. The results reveal the potential of deep learning in wind power and suggest that enhancing the field of view of neural networks can more effectively capture subtle pattern changes to reliably predict and prevent failures in complex environments [21, 22].

The essence of the research results lies in their specific contributions to wind farm operation, maintenance, and management practice. The high-speed convergence of the model implies that new data can be adapted more quickly in real-time fault monitoring and early warning systems, which is particularly important for dynamic wind farm operating environments [23]. In addition, its high accuracy rate indicates that the frequency of false alarms can be significantly reduced, and by accurately predicting potential failure points, it can provide valuable decision support for wind farm maintenance personnel, reduce unnecessary inspection and maintenance costs, and improve the safety and efficiency of wind farms.

Compared to the existing literature, the performance of the RFECNN model in fault diagnosis is superior to some traditional methods. For example, RFECNN can provide more accurate results when dealing with specific defects and anomalies in wind farms than deep neural network methods using spatial and temporal features and convolution neural network techniques based on continuous wavelet transform. Furthermore, RFECNN demonstrates superior learning efficiency and model stability in fault prediction and prevention when compared to the research on machine fault diagnosis that combines deep transmission and extreme learning machines.

The results show that the use of the RFECNN model to achieve the above results may be due to the natural advantages of CNN in feature extraction on the one hand. Field-of-view enhancement, on the other hand, improves the model's ability to capture anomalies in wind farms. Fault diagnosis and prevention lie in the ability to identify and learn from small changes in the operation of wind turbines, which often indicate potential failures [23]. The design of the RFECNN allows it to understand these changes more deeply, enabling accurate early warning of potential problems.

Through the application of RFECNN model, the accuracy of fault detection and the timeliness of preventive measures are significantly improved, which is of great significance for improving the operational efficiency and reliability of wind farms. The system is highly versatile and has the potential to be applied to other types of renewable energy systems, such as solar and hydropower. For these systems, the RFECNN model can similarly identify and predict potential failures through deep learning techniques to optimize maintenance schedules and reduce energy production disruptions. This cross-cutting application demonstrates the potential for adaptability and expansion of the approach across a wide range of renewable energy sectors, providing new perspectives and tools for future energy management and maintenance.

This study has limitations that should be considered. Firstly, the dataset used in the study is limited in scale and diversity, which may not fully capture all possible failure modes. This can limit the model's generalization ability and adaptation range [24]. Secondly, while the model performs well in current tests, its performance in actual complex operating environments can be impacted by several factors such as weather, environmental interference, and equipment aging. It is important to test the model's robustness under varying conditions, which requires further investigation. Additionally, optimizing the model's parameters and assessing its applicability to different types of wind farms are necessary to enhance its practical value [25, 26].

4 Conclusion

This study proposed a novel field of view enhanced CNN model for fault diagnosis and prevention in wind farms. The model demonstrated superior performance compared to traditional machine learning techniques (SVM and KNN) in terms of convergence speed, fault diagnosis accuracy, and stable power output improvement. The application of the model to a real wind farm case study showed its high consistency and accuracy in maintenance scheduling and economic benefit analysis. The study had two main contributions. Firstly, it developed a CNN-based system for fault diagnosis and prevention that can handle the complexity and variability of wind farm operating conditions. Secondly, it demonstrated the model's potential to enhance wind farm reliability, efficiency, and economy through accurate fault prediction and preventive maintenance.

However, there are some limitations that should be addressed in future research. First, the dataset used in the study is relatively small and homogeneous, which may limit the generalizability of the proposed approach to other wind farm settings. Future studies should collect and incorporate more diverse and large-scale fault data to improve the model's robustness and adaptability. Second, the practical implementation of the model in real wind farm operations requires further validation and optimization. Future work should focus on developing user-friendly interfaces and decision support tools to facilitate the adoption of the proposed approach by wind farm operators and maintenance crews.

In conclusion, this study contributes significantly to the field of wind farm fault diagnosis and prevention by proposing a novel CNN-based model and demonstrating its effectiveness in a real wind farm case. The proposed approach has the potential to greatly enhance the reliability, efficiency, and sustainability of wind energy systems, thereby contributing to the global transition to clean and renewable energy. Future research should build on the findings of this study and explore new directions in data-driven fault diagnosis, predictive maintenance, and intelligent wind farm management.

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