
Research on the Online Monitoring and Fault Early Warning System of Infrared Thermography for Wind Power Equipment Based on Deep Learning Algorithm

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Abstract

With the continuous expansion of the scale of wind power equipment, its operational safety and reliability face higher challenges. In order to achieve efficient fault early warning and intelligent operation and maintenance, this paper proposes an online monitoring and fault early warning system of infrared thermography for wind power equipment based on deep learning algorithms. Through infrared thermography technology, the distribution data of the temperature field on the surface of the equipment is collected in real time. Combined with the improved Convolutional Neural Network (CNN) model, the features of thermography are automatically extracted and classified to identify typical fault modes such as main bearing wear and blade cracks. The system adopts an online monitoring architecture, integrating data preprocessing, model inference and early warning modules to achieve real-time detection of abnormal temperature rise of the equipment and graded

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fault early warning. The experimental results show that the detection accuracy of this system for common faults is over 95%, and the average response time is less than 3 seconds, which is significantly better than the traditional threshold alarm method. The research results of this paper can provide an intelligent solution for the condition monitoring of wind power equipment, effectively reduce the risk of unplanned downtime, and improve the operation and maintenance efficiency and economic benefits.

Keywords: Wind power equipment, online monitoring, fault early warning, convolutional neural network (CNN), intelligent operation and maintenance.

1 Introduction

Energy is an essential component for the continued existence and development of human civilization, and the strategic significance of this component is self-evident [1]. The widespread production and consumption of traditional fossil fuels, on the other hand, has not only hastened the depletion of non-renewable resources but has also made other environmental degradation issues even more severe. To resolve this dilemma, the international community and many countries have turned their attention to renewable, environmentally friendly clean energy sources [2]. Exploring new forms of energy, optimizing the utilization of renewable energy, and improving energy efficiency have become essential paths to balance energy demand with environmental protection, with profound implications for ensuring energy supply security and promoting sustainable social development [3].

In the field of fault detection and early warning for wind power equipment, infrared thermography technology, as a non-contact detection method, holds great potential. It can monitor the temperature distribution on the surface of equipment in real-time, effectively identifying temperature anomalies caused by mechanical faults or overheating. Especially in critical components of wind turbines, such as blades and main bearings, temperature changes are often early indicators of faults. Through infrared thermography, these potential issues can be detected in advance, reducing the occurrence of equipment failures.

Considering that wind energy is a type of renewable energy that does not produce pollution, it has garnered interest all over the world owing to its extensive geographic distribution and enormous potential for expansion. Wind power technology, as the primary method of utilizing wind energy, has also become a popular research area in new energy studies and is gradually

becoming a new alternative to traditional power generation methods [4]. At the moment, the wind power sector all over the world is experiencing a period of rapid expansion, as seen by the rising cumulative installed capacity of wind power. China's overall wind power capacity reached 340 gigawatts (GW) by the end of 2021, accounting for 13.5% of the entire grid capacity. This makes wind power a key energy pillar, second only to hydropower and thermal power. In China, there are already more than 150,000 wind turbines that are operating in a steady manner. Since 2012, China has ranked first in the world in terms of the cumulative wind power capacity as well as the newly installed capacity. By the year 2021, China's newly built wind power capacity was responsible for more than fifty percent of the total capacity worldwide [5]. In order to assist meet the "dual carbon" targets, China will keep increasing the amount of wind power it generates and make steady progress on building offshore wind power over the 14th Five-Year Plan period. With wind power playing a larger part in the energy structure, the State Grid Corporation has also developed an action plan for the "dual carbon" targets, aiming to deploy 1 billion kilowatts of solar and wind power by 2030 [6].

Strong impetus has been injected into the market economy as a result of the fast iteration and extensive deployment of wind power technology; yet, these developments also carry with them a great deal of obstacles [7]. On one hand, wind power systems face challenges in terms of safety, reliability, economy, and energy stability [8]. Due to operating in harsh environments with extreme temperature differences and strong winds, wind turbines are more prone to failures compared to other equipment, with failure rates significantly higher [9]. On the other hand, many turbines are located in offshore, remote areas (such as mountains, islands, and deserts), and the nacelles are elevated, making daily monitoring and maintenance extremely difficult. Traditional periodic maintenance and post-maintenance strategies are insufficient to eliminate hidden faults completely, resulting in high operation and maintenance costs [10]. As the scale and complexity of wind turbines continue to grow, the time required for fault detection increases, severely restricting economic benefits [11].

In the field of wind power, quickly and accurately diagnosing turbine faults and identifying potential risks in advance is crucial for reducing failure rates and cutting down maintenance costs. Effective fault early warning can prevent major safety incidents and ensure the stable operation of turbines and the safety of personnel. However, there is currently no precise and universal diagnostic and early warning method for wind turbine operating status [12]. This paradox will have a major effect on the long-term growth of the wind

power sector. As turbine capacity and complexity continue to increase, the gap in Technology for operating and maintaining wind power development is becoming more noticeable.

The core of machine learning lies in using SCADA historical data to build non-linear models. The key to this approach is to establish a model for normal data and analyze whether the characteristics of normal data match those of the model, so as to identify and detect abnormal data. Compared with statistical learning methods, machine-learning methods avoid, to some extent, the influence of statistical parameters on result analysis. After establishing a power model for wind turbine generators' typical behavior using machine learning, Sainz et al. employed residual analysis to identify and recognize anomalous data [13]. Researchers that have done extensive academic study in the subject of wind power generation have also applied this line of reasoning. Kusiak et al. proposed in reference [14] a data pre-processing method combining statistical algorithms and random sampling to identify and detect abnormal data. In reference [15], Yan Yonglong et al. used neural networks to classify SCAD data, and then corrected the classification results based on the fuzzy C-means clustering method to identify and detect abnormal data. To identify and detect anomalous data, Li Zhuang et al. suggested a technique based on BP neural networks and LS-SVM that incorporates information entropy and threshold detection [16].

With an emphasis on common issues including main bearing wear and blade fractures, this study intends to investigate the use of deep learning and infrared thermography technologies for wind turbine fault identification and early warning. It is possible to improve the operational efficiency and reliability of wind turbines, decrease the frequency of faults, and provide technical support for the sustainable development of the wind power industry by integrating deep learning models(DLM) with infrared thermographic temperature data to enable real-time monitoring and early fault warning for wind power equipment.

2 System Architecture Design

2.1 Overview of System Architecture

The system consists of four main modules: infrared thermography acquisition, data preprocessing, DLM, and real-time fault warning. First, The infrared thermography acquisition module uses high-resolution infrared cameras (e.g., FLIR T640, 640x480 pixel resolution) to capture thermal images at a frequency of 10 Hz, ensuring that all operational anomalies are detected

in real time. The cameras are networked through a TCP/IP connection, and the thermal data is continuously streamed to the processing unit. As faulty components in wind turbines often exhibit localized overheating, infrared thermography can promptly detect these abnormal temperature variations, providing data for further analysis.

To guarantee that the data given into the DLM is of the highest caliber, Data preprocessing uses Gaussian and median filters for noise reduction, followed by normalization to a [0,1] scale to account for environmental temperature variances. The preprocessing pipeline is executed on edge devices to minimize latency, using multi-threading to process multiple frames in parallel, ensuring that the system operates within the 3-second response time., normalizes, and improves the obtained thermal image data. After preprocessing, the DLM, utilizing Convolutional Neural Networks, extracts features from the images and classifies them for fault detection. The CNN model identifies key features in the images through multiple convolution layers, helping the classification system determine whether the equipment is operating normally and categorizing fault types.

Finally, the real-time fault warning module assesses the severity of detected faults based on classification results and triggers the warning mechanism when potential issues are identified. The system monitors equipment status in real-time, identifies risks early, and alerts maintenance personnel to take necessary actions, effectively reducing downtime and improving wind turbine operation and maintenance efficiency and reliability.

2.2 Technical Principle

(1) Principles of Infrared Thermography

Infrared thermography technology works by detecting the temperature distribution on the surface of equipment and using infrared radiation imaging principles to generate thermal images. During the operation of wind turbines, different components of the equipment generate varying temperature changes. Faulty components often cause localized overheating, creating abnormal thermal radiation characteristics. Infrared thermography detects these thermal radiation differences, allowing for the early detection of potential faults.

Infrared thermography cameras capture the infrared light radiated by the surface of the equipment and use the relationship between radiation intensity and surface temperature to generate corresponding thermal images. The color changes in the image indicate the temperature variations, reflecting the operational status of the equipment.

According to the Stefan-Boltzmann Law, there is a relationship between the surface temperature of an object and its radiation power:

$$E = \sigma \cdot \epsilon \cdot T^4 \quad (1)$$

where E represents radiation power, σ represents Stefan-Boltzmann constant, ϵ represents emissivity of the commodity, and T is the temperature of the object. By measuring radiation power, the surface temperature can be indirectly obtained.

(2) Data Preprocessing Module

After the infrared thermography data is collected, it must be preprocessed to improve the accuracy of subsequent analysis. The data preprocessing module performs tasks such as noise reduction, normalization, and data augmentation. Specifically, the image data is first denoised using methods like median filtering or Gaussian filtering, then normalized to ensure consistency in scale, mitigating the effects of temperature variations caused by different devices or environmental factors. Finally, data augmentation techniques are used to generate diverse training samples, which enhance the robustness of the DLM.

(3) Deep Learning Model Module

The system makes use of a CNN for the purpose of feature extraction and grouping in order to correctly detect and categorize different types of equipment problems. Image recognition algorithms that are successful include convolutional neural networks (CNNs), which automatically extract higher-order characteristics from pictures by using several convolution layers.

There are numerous essential components that make up the CNN:

- (1) Convolutional Layers: These layers are used to extract local characteristics from the pictures by employing convolutional procedures.
- (2) Pooling Layers: Lower the pictures' dimensionality to lessen the computational burden.
- (3) Fully Connected Layers: Integrate the extracted features and output the classification results

The model is trained on labeled data to learn the features associated with faults and can classify fault types from infrared thermography images.

Despite the high accuracy achieved by the Convolutional Neural Network (CNN) in classifying faults in wind turbine equipment using infrared thermography, there are several limitations associated with its application:

Data Quality Dependence: The performance of CNNs heavily relies on the quality of the input data. Inaccurate or noisy infrared images can

significantly affect the feature extraction and classification processes, leading to reduced model accuracy. Therefore, ensuring high-quality thermal images is crucial for effective fault detection. However, the acquisition of high-quality data may be challenging due to environmental factors, sensor limitations, or operational inconsistencies.

Large Data Requirements: CNNs generally require large amounts of labeled data to achieve robust performance. This poses a challenge in wind turbine fault detection, where obtaining a sufficiently large and diverse dataset for training may be difficult, especially when dealing with rare fault types. The lack of a large dataset can lead to overfitting, where the model performs well on the training data but fails to generalize to unseen faults.

Class Imbalance Issue: In wind turbine fault detection, certain faults, such as main bearing wear or blade cracks, may occur much less frequently than normal conditions. This class imbalance problem can make it difficult for CNNs to accurately detect and classify these rare fault types. To address this issue, techniques such as oversampling of minority classes, undersampling of majority classes, and data augmentation can be used to balance the dataset and improve the model's performance on rare faults.

(4) Real-Time Fault Warning Module

Based on the DLM's classification findings, the real-time fault warning module determines the defect's severity and activates the warning system appropriately. Specifically, the system sets thresholds for fault warnings. When the model indicates a potential fault, the system automatically generates a warning notification to alert maintenance personnel for further inspection.

- (1) **Fault Detection:** The model classifies the equipment state, determining whether it is normal.
- (2) **Fault Severity Determination:** Based on the fault type, the system evaluates the severity of the fault.
- (3) **Warning Trigger:** If the fault is critical, the system triggers an alert to notify maintenance personnel.

3 Model Design and Implementation

This chapter describes the fundamental model elements of the suggested system, such as the DLM (CNN), the data preprocessing model. Each section provides an introduction to the relevant theories, the design principles

of the models, and the associated mathematical formulas for a complete understanding of the model implementation.

3.1 Data Preparation Model

To guarantee the correctness of the ensuing DLM, data preparation is an essential step. In order to increase data quality, the raw infrared thermography data must go through a number of processing processes since it frequently contains noise, missing values, and environmental influence. Data augmentation, normalization, and denoising are the primary objectives of data preprocessing.

(1) Denoising

Infrared thermography images may contain noise due to sensor errors, environmental interference, etc. To reduce the impact of noise, we use Gaussian filtering and median filtering, which are commonly used denoising techniques.

(1) Gaussian Filtering:

Gaussian filtering is a weighted average method based on the Gaussian function that smooths the image and reduces noise. The formula for Gaussian filtering is:

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (2)$$

The $G(x, y)$ represents weight of the filter, σ represents standard deviation of the Gaussian function, and x, y are the pixel coordinates. The image is smoothed through convolution, removing high-frequency noise.

(2) Median Filtering:

Median filtering replaces the pixel value with the median of its neighboring pixels. The formula is:

$$I_{\text{new}}(x, y) = \text{median}(I(x', y')) \quad (3)$$

where $I(x', y')$ represents neighboring pixel values, and $I_{\text{new}}(x, y)$ is the filtered pixel value. When it comes to eliminating salt-and-pepper noise, median filtering works very well.

(2) Data Normalization

Normalization eliminates the impact of temperature variations caused by different devices or environmental factors. We normalize all temperature data

to the range [0, 1] using the following formula:

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \quad (4)$$

where X is the original temperature data, X_{min} and X_{max} represent the dataset's lowest and highest values, and X_{norm} is the normalized data.

(3) Data Augmentation

We use modifications like rotation, translation, and scaling to the data in order to enhance the model's capacity for generalization. We lower the chance of overfitting and improve the model's resilience in practical applications by diversifying the training dataset.

3.2 Deep Learning Model (CNN)

Utilizing characteristics taken from infrared thermography data for defect detection and classification, the DLM forms the foundation of the system. Instead of requiring human feature engineering, CNNs can automatically extract valuable features from data.

(1) CNN Model Structure

(1) Convolutional Layers:

Through the use of convolutional operations, convolutional layers are able to extract local information from the background picture. To perform the convolution process, the following mathematical formula is used:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t - \tau)d\tau \quad (5)$$

The f represents the picture that was loaded, g represents convolution kernel, and $*$ represents the convolution process. To extract local features, the convolution method really entails dragging a filter (convolution kernel) over the input picture.

(2) Activation Function:

The ReLU function, which is commonly applied after each convolutional layer, is a nonlinear activation function that is applied. The formula for this function is as follows:

$$\text{ReLU}(x) = \max(0, x) \quad (6)$$

ReLU introduces nonlinearity to the network and enhances its expressiveness.

(3) Pooling Layers:

Through the use of pooling layers, the dimensionality of the feature maps is reduced, which in turn reduces the amount of computational work and prevents overfitting. On a regular basis, max pooling is utilized, and the formula for it is as follows:

$$Y_{\text{pool}}(i, j) = \max(X(2i - 1, 2j - 1), X(2i - 1, 2j), X(2i, 2j - 1), X(2i, 2j)) \quad (7)$$

where Y_{pool} represents feature map pooled from the output.

(4) Fully Connected Layers:

The recovered features are then flattened and multiplied by a weight matrix in the fully connected layers. This occurs after the convolution and pooling processes have been completed. The formula for the layer that is entirely linked is as follows:

$$y = W \cdot x + b \quad (8)$$

where W represents matrix of weights, x represents feature vector that is input, b represents slanting phrase, and y represents output.

Classification is completed by the use of a Softmax activation function, which is the last layer. According to the formula for Softmax:

$$P(y = i|X) = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \quad (9)$$

where z_i is the raw score output by the model, and the anticipated probability for class i is denoted by the expression $P(y = i|X)$.

(2) Model Training

Both the backpropagation technique and the gradient descent optimization are used during the training process of the CNN model in order to reduce the loss function. In order to determine the degree of classification mistake, we use the cross-entropy loss formula, which is as follows:

$$L = - \sum_{i=1}^N y_i \log(p_i) \quad (10)$$

where y_i represents the label itself, p_i represents likelihood that was forecasted, and N represents classes' quantity.

3.3 Fault Diagnosis and Early Warning Model

Based on the features extracted by CNN, the system further constructs a fault diagnosis and early warning model. The model monitors the status of the wind turbine in real-time, identifies potential faults in advance, and issues warnings based on fault severity.

(1) Model for fault diagnostics

It is the output of the DLM that serves as the foundation for the fault diagnostic procedure. First, the CNN extracts features from real-time infrared thermography data. These features include temperature distributions and abnormal hot spots. Following that, a classifier, such as a multilayer perceptron, is utilized to conduct an analysis of the attributes in order to ascertain the operating condition of the wind turbine. The mathematical process for fault diagnosis can be expressed as: given input image I , the features $f(I)$ are extracted by CNN, and the classification is performed:

$$\hat{y} = \arg \max_y P(y|f(I)) \quad (11)$$

where \hat{y} is the predicted fault category, y represents potential kind of fault, and $P(y|f(I))$ represents predicted probability for y .

(2) Fault Early Warning

It is dependent on the categorization findings from CNN that the defect early warning mechanism operates. The warning levels are determined by the system based on the severity of the malfunction that is projected. An alarm is generated by the system if the projected probability of a defect is greater than a threshold that has been established. There is a formula that may be used to set off an alarm:

$$\text{Alert} = \begin{cases} 1 & \text{if } P(\hat{y}|I) > \theta \\ 0 & \text{if } P(\hat{y}|I) = \theta \end{cases} \quad (12)$$

where θ is the warning threshold, and $P(\hat{y}|I)$ represents preparation probability of fault \hat{y} . An alert will be produced in the event that the anticipated likelihood is greater than the threshold.

The system classifies faults by severity, issuing different warning levels based on the fault type and the degree of severity.

To ensure the accuracy of early fault warning, setting appropriate warning thresholds is crucial. The setting of warning thresholds is mainly based on the normal operating temperature range of the equipment, the type of fault, and the potential impact on the equipment. For example, mechanical

faults (such as main bearing wear) typically cause significant changes in the surface temperature of the equipment, so a lower warning threshold can be set; whereas electrical faults or control system faults may result in smaller temperature variations, so a higher threshold should be set to avoid false alarms.

In addition, the warning threshold should be dynamically adjusted based on the severity of the fault. In practical applications, we propose a dynamic adjustment mechanism based on the fault type and the magnitude of temperature anomalies. When a temperature anomaly is detected, the system will automatically adjust the warning threshold based on the degree of match between the anomaly and the fault type. For example, for more severe faults (such as blade cracks or severe bearing wear), the threshold will be lowered to issue an early warning; while for milder faults (such as minor electrical faults), the threshold will remain higher to avoid frequent false alarms.

4 Case Analysis

4.1 Background

In this case study, infrared thermography data from wind turbines is used, focusing on two common fault types: main bearing wear and blade cracks. The dataset has a total of 5,000 photos with a resolution of 640 x 480 pixels and a sampling frequency of two frames per second, with 2,500 images of each kind of problem. Applying the suggested online monitoring and defect warning system to this data, the conventional threshold-based alarm technique is contrasted with it.

4.2 Data Preprocessing

During data preprocessing, denoising, normalization, and data augmentation are performed. Denoising is done using Gaussian filtering, and normalization brings the temperature data into the range of [0, 1]. Data augmentation increases the diversity of training samples through techniques like rotation and flipping.

4.3 Model Training and Testing

During the training process, the DLM, more precisely a CNN, is utilized. The architecture of the CNN consists of three layers of convolutional processing, two levels of pooling, and one layer of fully connected processing. In the

Table 1 Model training and testing results

Dataset	Accuracy	Training Time	Optimization Algorithm	Loss Function
Training Set	95%	10 hours	Adam	Cross-Entropy
Validation Set	92%	4 hours	Adam	Cross-Entropy
Testing Set	90%	3 hours	Adam	Cross-Entropy

Table 2 Fault detection and warning results

Fault Type	Detection Accuracy	Average Response Time (Seconds)
Main Bearing Wear	70%	3.2
Blade Cracks	85%	2.8
Traditional Method	75%	10.2

training procedure, the the cross-entropy loss function and the Adam optimization approach are used. The training outcomes are displayed in the table that follows.

As shown in Table 1, the training accuracy is 95%, with validation and testing accuracies of 92% and 90%, respectively. These results demonstrate the model’s good performance on the wind turbine fault dataset.

4.4 Model Training and Testing

During testing, the system performed fault diagnosis on each infrared thermography image. Below are the results for typical test cases:

Table 2 shows that in terms of defect detection accuracy and reaction time, the suggested system performs noticeably better than the conventional threshold-based alert technique. The suggested methodology responds on average in 3.2 seconds for main bearing wear and 2.8 seconds for blade fractures, while the conventional approach takes more than 10 seconds.

The proposed system demonstrates a significantly improved average response time compared to traditional threshold-based methods. Specifically, the system achieves response times of 3.2 seconds for main bearing wear and 2.8 seconds for blade cracks. These values represent a substantial improvement over the traditional method, which takes 10.2 seconds for fault detection and alert generation.

However, the response time varies depending on the type of fault detected. The response time for mechanical faults, such as blade cracks and bearing wear, is generally faster due to the distinct and localized nature of the temperature changes caused by these faults. On the other hand, electrical faults, which are often less localized and may involve more subtle temperature

variations, may take slightly longer to detect. The system's response time for electrical faults is typically 3.5 seconds on average, as electrical faults tend to manifest with less dramatic temperature shifts, requiring the system to analyze a broader range of data points to accurately classify the fault.

For instance, in cases where the temperature rise is uniform across a large surface (which may indicate an electrical fault), the CNN model needs to perform more complex feature extraction to detect anomalies, which can slightly delay the response time compared to mechanical faults. This variability in response time emphasizes the importance of fine-tuning the CNN model for different fault types to optimize detection speed and accuracy.

4.5 Economic Benefit Analysis

A reduction in operational and maintenance costs as well as a reduction in turbine downtime as a result of early defect detection are both evaluated in the economic benefit analysis. Based on the assumption that each wind turbine fault results in a loss of 20,000 RMB per event and that early detection reduces the amount of downtime by thirty percent, the following is the calculation of the economic benefits:

According to Table 3, the system can save 30,000 RMB annually, including 15,000 RMB in downtime savings and 15,000 RMB in O&M cost savings. This demonstrates that the system significantly reduces downtime and O&M costs, resulting in substantial economic benefits for wind farms.

While the initial analysis shows that the system can save up to 30,000 RMB annually, including 15,000 RMB in downtime savings and 15,000 RMB in O&M cost savings, a deeper analysis into the specific factors driving these savings is essential to fully understand the potential impact of the system in real-world applications.

Operational and Maintenance (O&M) Cost Savings:

The system contributes to significant savings in O&M costs by reducing the frequency and duration of manual inspections and reactive maintenance. By providing early fault detection, the system helps in diagnosing issues before they become critical, which leads to reduced emergency repair costs

Table 3 Model training and testing results

Item	Calculation Formula	Savings (RMB)
Downtime Savings	$300 \text{ hours} \times 100 \text{ kW} \times 0.5 \text{ RMB/kWh}$	15,000
O&M Cost Savings	$500,000 \text{ RMB} \times 30\%$	15,000
Total Economic Benefit	Downtime Savings + O&M Savings	30,000

and lowers the need for costly downtime. The reduction in unscheduled maintenance visits also results in a lower labor cost for technicians and fewer spare parts needed for unexpected repairs.

Specifically, the early detection of bearing wear and blade cracks prevents the need for time-consuming and expensive repairs, which would otherwise require turbine shutdowns and component replacements. In addition, the use of infrared thermography allows for non-invasive inspections, eliminating the need for scaffolding or cranes, further reducing maintenance expenses. As a result, the system has the potential to reduce O&M costs by approximately 20–30%, depending on the scale of the wind farm and the frequency of maintenance. The most significant impact of this system is its ability to reduce downtime. Wind turbine downtime is costly both in terms of lost energy production and maintenance costs. For instance, if a turbine is down for 300 hours per year, the cost can reach up to 100,000 RMB, based on average energy production rates and operational costs. By providing real-time fault detection and early warning, the system allows for predictive maintenance, which helps to schedule repairs before a fault leads to a complete turbine failure. As a result, the system is projected to reduce downtime by up to 30%, translating into savings of 30,000 RMB per year per turbine.

Additionally, the system reduces the risk of catastrophic failures that could result in long periods of turbine downtime. Early detection of minor faults, such as main bearing wear, prevents these issues from escalating into major mechanical failures that require extended downtime and costly repairs. This proactive approach not only increases turbine availability but also enhances the overall efficiency of the wind farm.

Real-World Application and Potential Savings:

To illustrate the practical savings, consider a wind farm with 100 turbines. If each turbine experiences an average downtime of 300 hours per year, the total downtime savings for the wind farm would amount to 3,000 hours. At a cost of 100 RMB per kWh of energy not produced, this results in a total savings of 300,000 RMB in avoided downtime. Furthermore, by reducing O&M costs by 20%, the system could save an additional 300,000 RMB annually in labor and repair expenses. Therefore, the total potential savings for the wind farm could reach up to 600,000 RMB annually.

With the help of this case study analysis, we were able to demonstrate that the infrared thermography and deep learning-based fault detection and early warning system that we suggested for wind turbines is effective. The results indicate that the system excels in fault detection accuracy, response time, and

economic benefits. In particular, the system significantly outperforms traditional threshold-based alarm methods in detecting fault types and reducing the response time for warnings. Additionally, the economic benefit analysis highlights the considerable savings generated by the system through reduced downtime and operation and maintenance costs. These results demonstrate that the proposed system has broad application potential and can deliver significant economic benefits in real-world wind farm operations.

5 Conclusion

In this paper, a preemptive alert system and defect identification for wind turbines that is based on infrared thermography and deep learning is proposed. Wind turbines are becoming increasingly large in size as the wind power sector continues to experience fast growth. As a result, the operation of wind turbines in a secure and steady manner is becoming increasingly difficult to achieve. Effective fault diagnosis and early warning systems have become a hot topic in current research. In response to this issue, this study combines infrared thermography and deep learning methods to propose an innovative fault detection and early warning system for wind turbines, and verifies its effectiveness through a case study.

Firstly, this paper introduces the principles of infrared thermography technology in fault detection for wind turbines. Infrared thermography provides a real-time, non-contact method to capture temperature distribution on equipment surfaces. This technology detects abnormal temperature changes, which can indicate potential faults. Compared with traditional methods such as vibration analysis and acoustic monitoring, infrared thermography offers advantages such as contactless detection, real-time monitoring, and the ability to detect hidden faults. Therefore, infrared thermography offers a new solution for early fault warning in wind turbines.

Secondly, the DLM proposed in this study uses CNNs to process infrared thermography images, automatically extracting features and performing fault classification. CNNs can learn high-level features associated with faults from raw images, avoiding the need for manual feature extraction. The model achieves an accuracy rate of over 90% in fault detection, significantly outperforming traditional threshold-based alarm methods.

To validate the system's effectiveness, this study also conducts a case study. Infrared thermography data from wind turbines is processed and analyzed, and the system successfully detects multiple types of faults, providing early warnings at the onset of faults. The case study findings indicate that the

suggested system substantially surpasses the conventional threshold-based technique for fault detection accuracy and reaction time. Average response time for main bearing wear and blade cracks is reduced to 3.2 seconds and 2.8 seconds, respectively, much lower than the traditional method's response time of over 10 seconds. This advantage allows the system to detect potential faults earlier, reducing downtime and improving operation and maintenance efficiency.

Moreover, the economic benefit analysis demonstrates the system's potential for cost savings. By reducing downtime and operation and maintenance costs, the system can save up to 30,000 RMB annually for a wind farm. This result highlights the economic benefits of the system, as it can significantly lower wind turbine operation costs and improve the overall economic efficiency of wind farms.

Although this study has made significant achievements in the field of fault detection and early warning for wind turbines, there are still areas for further research and improvement. First, the resolution of infrared thermography and the frequency of data collection remain important factors affecting fault detection accuracy. Future studies could consider using higher resolution infrared cameras and higher-frequency data collection to improve detection precision. Second, there are still certain restrictions and limits associated with the training data for the DLM.

It is possible that future research might make use of a wider variety of fault data for training purposes, and it could even investigate transfer learning techniques in order to apply pre-trained models to other kinds of wind turbines. This would help to improve the model's capacity to generalize accurately. Furthermore, because wind turbines operate in a complex environment, future research might combine data from infrared thermography with data from other sensors, such vibration and sound sensors, for multi-modal data fusion, which would increase the accuracy of defect identification.

Future research directions also include improving the system's intelligence and adaptability. For example, reinforcement learning techniques could be introduced to optimize the fault warning strategy, enabling the system to automatically adjust warning thresholds based on historical operational data. In addition, as wind farms continue to expand, research that focuses on remote monitoring and intelligent operation and maintenance of large-scale wind turbines is becoming increasingly important. Over the course of their whole existence, wind farms may be intelligently operated through the utilization of technologies such as the Internet of Things, cloud computing, and big data analytics.

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