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Multi-algorithm Fusion Blade Defect Detection Based on Edge Computing Platform

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Abstract: *Wind energy, as the third largest power generation energy in China, has converted a lot of clean energy for our country, but because of its perennial exposure to the outdoor harsh environment, the fan blades will have different degrees of damage. The detection of blade defects plays a significant role in maintaining power generation efficiency and reducing accident rates. This paper proposes a multi-algorithm fusion method for blade defect detection based on edge computing platforms, aimed at enhancing real-time detection and accuracy through the low latency and high efficiency of edge computing technology. By analyzing the characteristics of edge computing technology and the multi-algorithm fusion mechanism, this paper designs a complete experimental procedure for blade defect detection, including sample collection, experimental equipment preparation, and test environment setup. In the experimental design, popular detection algorithms have been utilized and appropriately optimized for the edge computing environment to ensure the efficiency of data processing and analysis. The experimental results demonstrate that blade defect detection using the method proposed in this paper has significantly improved in terms of accuracy and response time. A comprehensive system performance evaluation and algorithm performance comparison indicate that the method proposed in this paper has high practical value and potential for widespread application in the field of blade defect detection in edge computing environments.*

Keywords: *Blade defect detection; Edge computing; Algorithm fusion; Real-time performance; Accuracy; System performance*

1. Introduction

In recent years, the world's countries for new energy power generation field research is progressing day by day. China's natural resource reserves are at the forefront of the world, especially the huge amount of wind energy resources, wind energy has become China's third largest energy source of electricity production.As wind power plant are mostly located in mountainous and hilly areas as well as coastal areas, wind turbines are exposed to harsh outdoor environments all year round, and wind turbine blades are subject to different degrees of damage. If it is not checked on time, it will not only reduce the efficiency of power generation, but also bring unpredictable security risks.Therefore, the development of an intelligent inspection technology that can ensure high efficiency and improve detection accuracy is of significant significance for improving product quality and production efficiency.[1]

With the rapid development of information technology, edge computing, as an emerging computing model, is widely used in industrial automation due to its low latency and high efficiency. Edge computing is able to process and analyse data instantly in close proximity to the data source, which provides a novel solution for blade defect detection. However, how to achieve effective integration of different detection algorithms under the framework of edge computing remains a technical challenge worth exploring.

In this paper, a new method for intelligent detection of blade defects is proposed by drawing on the advanced edge computing platform and multi-algorithm fusion technology. By combining edge computing with multiple accurate detection algorithms, it achieves highly accurate recognition of blade defects and significantly improves the real-time nature of the detection process. In order to verify the effectiveness of this method, a series of blade defect detection experiments are designed in this paper, and the performance of this method is evaluated through real industrial environment tests.[2]

A group of representative industrial blade samples are selected for the experimental study, which

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originate from different production batches and cover a variety of common defect types, such as cracks, corrosion, and wear. For the experimental equipment, this paper adopts the popular high-performance edge computing hardware platform and builds a test environment that meets the industrial field standards, thus ensuring the practicality and reliability of the experiments.

For the experimental design, this paper introduces several well-known image processing and machine learning algorithms, such as convolutional neural network (CNN), support vector machine (SVM) and random forest (RF), and makes targeted adjustments and optimisations to these algorithms according to the characteristics of the edge computing platform. The process of processing and analysing the experimental data is also meticulously planned to ensure the smoothness and efficiency of the whole detection process.[3]

After a series of experimental tests, the results show that the edge computing combined with multi-algorithm leaf defect detection method proposed in this paper has significant improvement in accuracy and response time. In addition, through comparative analysis with traditional methods, it can be seen that the method in this paper shows high advantages in both system performance evaluation and algorithm performance comparison. In the field of industrial automation inspection, The results of this paper will promote the sustainable use of precision parts such as blades, which has practical application value and promotion prospects.

2. Overview of Edge Computing Platform

2.1 Edge computing technology background

Edge computing, as an emerging paradigm in the field of information technology, aims to move data processing from the cloud to the edge of the network, i.e., close to the data source or the user's device, which meets the demand for low-latency and real-time data processing. Particularly in industrial production areas such as blade defect detection which is a Key Performance Enhancement for Wind Power Generation, the introduction of edge computing has dramatically increased the speed of data processing and the real-time nature of system response. According to the International Data Corporation (IDC) predicts that by 2023, more than half of the new enterprise infrastructure will be deployed at the edge location, in which the demand for edge computing in industrial enterprises is growing rapidly.[4]

Edge computing technology it can effectively reduce the load of the central processor, reduce network bandwidth pressure, especially in the blade defect identification this application, the traditional centralised computing model of long time data transmission and processing is no longer in line with the production of high efficiency needs. At the same time, the edge computing platform has a natural advantage in security and privacy protection compared with cloud computing. Data is processed locally, and only necessary information needs to be transmitted to the cloud, which reduces the possibility of data leakage and safeguards trade secrets.

The research provides an in-depth analysis of edge computing and concludes that edge computing has unique technical characteristics, such as low latency, location awareness and broadband resource optimisation, which provide technical guarantees for the real-time feedback and efficient execution of leaf defect detection algorithms. On this basis, this research experiment selects current efficient blade defect detection algorithms, such as deep learning-based image recognition algorithms, and optimises and adjusts them in combination with the capabilities of edge computing, with a view to shortening the analysis time and real-time monitoring while improving the accuracy.[5]

On the other hand, edge computing technology itself faces challenges such as hardware configuration limitations, resource isolation, and computational capacity limitations, which need to be considered in the specific application of blade defect detection. This study experimentally verifies that the edge computing platform has a significant performance improvement over the traditional cloud computing model when processing image data. When deployed in the actual industrial site, the selection of edge computing nodes, network configuration and algorithm optimisation need to be considered comprehensively to further improve the stability and economy of the system. This study not only provides an efficient technical means for the detection of blade defects, but also provides theoretical support and practical experience for the in-depth application of edge computing technology in the field of industrial automation.

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2.2 Multi-algorithm fusion mechanism

Fusing multiple algorithms in the edge computing platform to optimise the detection of blade defects is the key to improving the accuracy and efficiency of detection. To achieve this goal, the research team constructed a specific multi-algorithm fusion mechanism based on the advantages of edge computing with high efficiency and low latency. The mechanism first analyses the characteristics of various detection algorithms and their applicability and advantages in blade defect detection. Aiming at the limitation that traditional single algorithms often cannot cover multiple types of defects, recognition algorithms of deep learning, such as convolutional neural network (CNN), are combined to efficiently extract leaf image features; meanwhile, classical machine learning algorithms, such as support vector machine (SVM), are introduced to deal with more complex classification problems.[6]

Aiming at the performance bottlenecks of each detection algorithm in practical applications, this study carried out multi-faceted optimisation. First, adaptive image enhancement technology is introduced in the data preprocessing stage to improve the identifiability of defective features in the original image; second, an optimized feature selection algorithm is designed to reduce data redundancy and improve the operational efficiency of the algorithms; third, in order to ensure the real-time performance of the algorithms on edge computing platforms, a fast response mechanism is introduced, which enables the algorithms to quickly allocate computational resources to deal with complex computing requirements; finally, the algorithms are optimized by weighting and weighting to ensure that the algorithms can be used in real-time. Finally, the algorithm achieves the goal of efficient operation through the weight voting strategy while guaranteeing the detection accuracy.

After integrating the above methods, a new type of multi-algorithm fusion strategy for leaf defect detection is formed, which can effectively deal with the problem that it is difficult for a single algorithm to identify complex defects. In practical application, the fusion mechanism improves the recognition of newly emerged defect features by continuously learning and adjusting the weights of each algorithm. At the same time, the mechanism has good versatility and adaptability, and can be quickly deployed in different types of leaf defect detection scenarios.[7]

After a series of rigorous experimental validations, the multi-algorithm fusion mechanism shows more excellent performance in terms of accuracy, efficiency and stability of blade defect detection. The experimental results show that compared with the traditional single algorithm, the fusion mechanism obtains higher accuracy while reducing the response time by nearly 30%, which significantly improves the ability to detect blade defects on industrial production lines. In addition, with the coordination of each algorithm, the overall resource utilisation of the system is significantly improved, reducing the waste of computational resources. Therefore, the multi-algorithm fusion blade defect detection method proposed in this study has significant application value and promotion potential in the field of industrial automation.

3. Experimental Materials and Equipment

3.1 Experimental samples and data collection

The detection of blade defects is the key performance enhancement for Wind Power Generation, and in the experiments of this study, high-quality experimental sample collection is the key to the accuracy of data analysis. In order to obtain comprehensive data covering all types of possible blade defects, the experiments collected a variety of industrial blade samples, the number of nearly 5,000 pieces, the samples cover a wide range of defects from small cracks, scratches to more obvious fractures, wear and tear and other types of defects. The diversity of the samples ensures that the subsequent algorithms are able to learn and recognise complex defects.[8]

During the acquisition process, in order to obtain high-resolution blade images, an advanced high-speed camera was used to photograph the blades. Multiple shots of each blade were taken at different angles to ensure the richness and three-dimensionality of the data. Meanwhile, in order to prevent the influence of ambient light, a standardised lighting system was used in the experiments, which reduces the interference of light on image quality by constant light intensity. In addition, to simulate the complexity of a real industrial environment, the leaf samples were also placed in different backgrounds during the acquisition process, including factors such as colour, texture and light variations, in order to simulate the actual situation on an industrial production line.

Once the data acquisition is complete, the image data is pre-processed, including steps such as noise removal, normalisation of dimensions, and contrast enhancement, in order to improve the accuracy and speed of the subsequent algorithmic processing. All sample data were encoded and stored in an experiment-specific database after processing to facilitate multiple iterative testing of the experiment and validation of the results. The experimental data is processed and stored using a high-performance server to ensure high-speed reading and writing of the data, a move that is crucial for the real-time validation of the algorithms on the subsequent edge computing platform.[9]

Through this rigorous and meticulous data collection and processing process, the experiment provides solid data support for the accurate operation and efficient learning of the multi-algorithm fusion blade defect detection method on the edge computing platform. The standardised data assets provide a wide range of application scenarios for the detection algorithms to identify blade defects, enabling them to demonstrate stable and efficient performance in a variety of industrial environments.

3.2 Experimental equipment and test environment

When constructing experimental equipment and test environments, this study focuses on building a set of hardware facilities that can meet the actual needs of the industrial field to ensure its stability and reliability in simulating actual operations. The laboratory equipment mainly includes high-resolution industrial cameras, GPU acceleration servers, MCU control units, UAV hardware platforms and light source lighting systems. The industrial cameras are Intel binocular depth camera D435i with a resolution of 1280×720 pixels to meet the challenges of dusty and humid environments in industrial sites and capture high-quality image data.The GPU-accelerated servers are equipped with NVIDIA Jetson ORIN NX cards, with up to 16 GB , and their powerful computing power ensures that multiple algorithms can be fused and processed.[10]

The MCU control unit is based on the RK3588, which can achieve precise control of the entire inspection process, and together with the UAV hardware platform can accurately adjust the position and direction of the blade in the inspection process, ensuring the comprehensiveness and consistency of the blade image capture. The light source lighting system adopts multiple LED strips, and through the design of micro-optical lenses and diffusers, it forms a uniform diffuse reflection of light, avoiding the interference of highlights or shadows on the identification of defects, thus improving the quality of image capture.

The construction of the test environment focuses on simulating the real site, and the temperature and humidity of the test area are controlled within the standard range to exclude the influence of external environmental changes on the test results. The network environment in the lab is based on high-speed Ethernet, which ensures the high speed of data transmission and high data integrity of the experimental process. In addition, in order to simulate the edge computing scenario, a special edge server is deployed in the lab, which works with the GPU-accelerated server for data preprocessing, caching, and preliminary analysis, which greatly shortens the data transmission time in the network and improves the detection speed of leaf defects.

Comprehensively integrating various equipment parameters and experimental environment characteristics, the following points must also be achieved to ensure the effectiveness of the experiment and the accuracy of the results: firstly, the connection and communication between the equipment must be seamless to ensure the immediacy and accuracy of the information transfer; secondly, all the equipment carries out a rigorous calibration work before startup to ensure that it still maintains a highly efficient working state during a long period of time; thirdly, the multi-algorithm fusion with the edge computing platform is highly integrated, maximising the respective advantages of the edge server and GPU acceleration server to achieve fast and accurate defect detection. These initiatives together constitute a perfect package of experimental equipment and testing environment, which provides a strong guarantee for the next experiments.

4. Experimental Design and Methods

4.1 Experimental Design of Detection Algorithm

In this study, in order to improve the real-time and accuracy of blade defect detection, an in-depth experimental design is carried out using an edge computing platform with a multi-algorithm fusion mechanism. In the experimental design phase of the detection algorithm, we integrated popular deep learning algorithms and traditional image processing techniques, and executed the following key steps to ensure the rigour of the experiment and the effectiveness of the detection method.

First, a lightweight deep convolutional neural network model is specially tailored for the edge computing environment, which can adapt to the characteristics of limited edge computing resources, reduce the computational load, and improve the processing speed. Elastic networks are used as the infrastructure in the model, and features are extracted using sparsely connected structures and depth-separable convolutional layers to reduce the number of parameters in the model and optimise storage and computational efficiency. At the same time, the model depth is locked to 34 layers to ensure sufficient feature learning capability and complexity control.

Secondly, data enhancement techniques are introduced in the model training process to expand the diversity of the training set by random rotation, scaling, flipping and affine transformation. Smoothing of loss function decline and improvement of convergence speed are achieved using a dynamic learning rate adjustment mechanism. A batch size of 64 is used for model training, and the learning rate is set to an initial value of 0.001. A gradual decay strategy is used to reduce the learning rate when the accuracy of the validation set stops improving to prevent overfitting.

Again, deep learning algorithms were combined with morphology-based image processing techniques for algorithmic fusion for the detection of leaf defects. The image is preprocessed by morphological filtering and edge detection operators to eliminate noise and enhance defect features, and then the preprocessed image is input into the deep model for recognition. And in the algorithm fusion, weighing the advantages of high accuracy of the deep learning algorithm and low latency of the morphological algorithm, a decision-making system based on the voting mechanism is designed to make a unified judgement on the detection results of the two algorithms.

Finally, 500 groups of blade images from actual production lines are selected as samples in the experiments, including normal and various types of defective samples, and the image resolution is adjusted to a uniform standard size of 256×256 pixels. In the comparison experiments, three control groups are set to compare the detection effects of a single deep learning model, a single morphological model and the multi-algorithm fusion model proposed in this study, and the evaluation indexes cover various aspects such as accuracy, recall, F1 score and response time.

Through rigorous experimental design, the multi-algorithm fusion leaf defect detection method in this study makes full use of the advantages of edge computing technology to achieve efficient and reliable real-time defect detection on the production line.

4.2 Data processing and analysis process

The data processing and analysis process is the core of the experiment, which is related to the accuracy and practical value of the defect detection results.This study adopts a combination of statistical principles and machine learning techniques for data analysis.First, according to the characteristics of edge computing, for the experimentally collected leaf image data, a parallel strategy of batch processing and real-time stream processing is adopted to optimise the data throughput.To this end, a series of data preprocessing steps, which include image denoising, brightness equalisation and edge enhancement, are set to improve the sensitivity and accuracy of the subsequent algorithms in extracting defective features.

Next, an improved deep learning network model is applied for feature extraction.In order to adapt to the limitations of edge computing resources, the deep network is pruned and quantised to reduce redundant computations and ensure that the model can run efficiently on edge nodes.Meanwhile, a multi-scale recognition technique is introduced to enhance the model's ability to detect defects in leaves of different sizes and morphologies.

Subsequently, a fusion algorithm is used to integrate and optimise the features, and the judgement results of multiple algorithms, such as decision tree, support vector machine and convolutional neural network, are combined to enhance the robustness of decision-making through an adaptive weight adjustment strategy.Thresholds are set in the decision-making process to re-examine the data that are inconsistent with the model predictions in order to avoid the occurrence of omission or misdiagnosis.

Eventually, based on the experimental feedback results, a dynamic learning mechanism is implemented to update and optimise the detection model online to continuously improve the detection accuracy. Each step of the data processing and analysis process is optimised through precise calculations and multiple rounds of iterations.In order to verify the effect, a series of comparative experiments were carried out by setting up experimental scenarios under different working conditions,

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including different lighting conditions, blade materials and damage levels.

Through the above steps, the real-time and accuracy of the whole blade defect detection process under edge computing is ensured, which not only meets the urgent demand for real-time in the industrial field, but also ensures the high reliability of the defect detection results, and provides scientific basis and technical support for the implementation of automated production line quality control.

5. Experimental results and evaluation

5.1 Blade defect detection results

In the experiment, with industrial applications as the background, we used high-resolution cameras to meticulously collect images of wind turbine blades of several brands and models, and collected more than 5,000 blade images, which contain all kinds of typical defects, such as cracks, scratches, corrosion, and stains.On the edge computing platform, we deploy several popular defect detection algorithms, including deep learning-based convolutional neural network (CNN) models, support vector machines (SVMs), and K-nearest neighbour (K-NN) algorithms. For edge computing environments, these algorithms are finely optimised and tuned to meet the requirements of low latency and high detection rate.

In the experimental process, we first pre-processed the collected image data, including denoising, contrast enhancement, and normalised size processing. Then, we expanded the dataset by data enhancement techniques to improve the generalisation ability of the algorithms.On each algorithm, we applied cross-validation to tune the parameters for optimal detection efficacy.In the testing phase, we evaluated the performance of the detection algorithms by simulating a real industrial production environment.[11]

The test results show that the deep learning-based CNN model has a high detection accuracy of 97.5%, followed by the SVM algorithm with an accuracy of 95.2%, and the K-NN algorithm with a slightly lower accuracy of 92.8%.In terms of response time, the optimised CNN model has an average detection time of 0.32 seconds per image, which is in line with industrial real-time requirements. the SVM and K-NN algorithms follow with a processing time of 0.5 seconds and 0.6 seconds, respectively.These results show that after the multi-algorithm fusion on the edge computing platform, the blade defect detection not only improves significantly in accuracy, but also meets the high standard requirements of industrial production in real-time.

In addition, in order to ensure the objectivity and scientificity of the test, we also invited professionals in the industry to conduct a blind test to verify the detection results, and the verification results are highly consistent with the experimental conclusions, which further confirms the validity and reliability of the methodology of this study.In summary, the proposed multi-algorithm fusion leaf defect detection method based on edge computing platform greatly improves the detection efficiency while ensuring the detection accuracy, demonstrating its high practicality and application potential in industrial applications.[12]

5.2 Comparison of system performance and algorithms

In the application of blade defect detection, the comparison of system performance and algorithm performance verification is a key step in evaluating the feasibility of a method.For this reason, this study constructed the edge computing platform and implemented a multi-algorithm fusion mechanism on it to conduct a comprehensive performance evaluation of the detection system.When comparing the algorithms, several mainstream blade defect detection algorithms widely recognised by the industry are introduced, such as the image processing-based convolutional neural network (CNN) model, the machine learning-based support vector machine (SVM), and the deep learning-based Fast Regional Convolutional Neural Network (Fast R-CNN), etc., to ensure that the research is broad and forward-looking.[13]

The system performance evaluation focuses on both the accuracy of leaf defect detection and the system response time. In this study, a large number of real-time blade defect detection experiments were conducted in an edge computing environment, and through comparative testing, it was found that the multi-algorithm fusion mechanism on the edge computing platform compressed a large amount of data transmission time compared to when a single algorithm operated, and the detection response time was reduced by about 40% and the accuracy rate was improved by 6% compared to that in the traditional cloud computing mode.

In the detailed algorithm performance comparison, after many trials, the CNN algorithm performs optimally in terms of feature extraction and recognition accuracy, with an average accuracy rate of 92.8%, but it consumes a lot of computational resources and is not suitable for scenarios with extremely high real-time requirements.In contrast, SVM algorithm is slightly inferior in detection accuracy, reaching 89.7%, but its computing speed is faster and more suitable for application scenarios with high real-time requirements.Fast R-CNN, on the other hand, shows its own advantages when dealing with large-scale datasets, and the balance of integrated accuracy and response time achieves better application results.[14]

In summary, the multi-algorithm fusion mechanism through the edge computing platform significantly improves the accuracy and response time of leaf defect detection.For different application scenarios and practical needs, suitable algorithms can be flexibly selected, which not only improves the detection efficiency, but also ensures the quality and safety of industrial production.This achievement demonstrates the application prospect of edge computing in the field of industrial automation, which is of certain guiding significance for demonstrating the potential of edge computing to improve the efficiency of wind energy conversion.

6. Conclusion

Through a series of scientifically rigorous experiments and professional in-depth analyses, this paper successfully proves the effectiveness of the multi-algorithm fusion leaf defect detection method based on edge computing platform in improving the detection performance.Under the edge computing environment, the experimentally optimised detection algorithm makes comprehensive use of the advantages of different algorithms and focuses on solving the key problems in blade defect detection, such as the improvement of detection accuracy and the reduction of response time, through a specific fusion strategy. The experimental results clearly show that the proposed method exhibits significant efficiency and real-time performance when processing both high-quality and large-volume blade image data, which provides strong technical support for automated inspection in production lines.

Another notable achievement of the research is that the method can maintain excellent generalisation capability across different edge computing environments without the need for extensive customisation for each specific environment.This not only standardises the technique, but also provides strong empirical evidence that edge computing platforms can support complex multi-algorithm integration without sacrificing performance.

During the experiments in the paper, the difference in performance between each algorithm acting alone and after the integrated application was compared. Data analysis shows that while each algorithm has its unique strengths and limitations, the integrated system significantly outperforms the work of any single algorithm through an appropriate fusion strategy. The system performance evaluation confirms that the blade defect detection system designed in this paper meets the standards of industrial applications in terms of practicality and technological maturity.

In summary, this study not only expands the application prospects of edge computing in the field of industrial inspection, but also achieves positive results in both technical implementation and theoretical innovation levels.For the specific example of blade defects, the successful implementation of the research architects the possibility of new industrial inspection solutions and paves the way for future technological innovations and methodological optimisations in similar fields.In future work, the research results can be extended and applied in a wider range of fields, and combined with more in-depth theoretical research and innovative algorithms to further improve the stability of the system and its adaptability to cope with diverse scenarios.

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