Deep Learning-Based Image Recognition Technology for Wind Turbine Blade Surface Defects

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***Abstract*—This paper proposes WindDefectNet, an image recognition system for surface defects of wind turbine blades, aiming at solving the key problems in wind turbine blade maintenance. At the beginning of the system design, the functional requirements and performance index requirements are clarified to ensure the realization of the functions of image acquisition and preprocessing, defect detection and classification, defect localization and size measurement, and to emphasize the key performance indexes such as accuracy, recall, processing speed and robustness of the system. The system architecture consists of multiple modules, including image acquisition and preprocessing module, feature extraction module, attention enhancement module, defect detection module, etc., which work together to achieve efficient defect recognition and localization. By adopting advanced deep learning techniques and model design, WindDefectNet is able to maintain high accuracy and stability in complex environments. Experimental results show that WindDefectNet performs well under different lighting conditions, shooting angles, wind speed and weather conditions, and has good environmental adaptability and robustness. The system provides strong technical support for blade maintenance in the wind power industry.**

***Keywords*—Wind turbine blades; image recognition; defect detection; deep learning; WindDefectNet**

I. Introduction

With the growing global demand for renewable energy, wind power, as an important clean energy source, has been developing rapidly worldwide. According to statistics, by the end of 2023, the global installed capacity of wind power reached about 800GW, and is expected to grow to at least 1,200GW by 2030 [1]. China, as one of the largest wind power markets in the world, has an installed capacity of more than 250GW, and is still growing at a high rate every year. This rapid growth not only promotes the progress of wind power technology, but also brings higher requirements for efficient and reliable operation of wind power equipment.

Wind turbine blades are an important part of wind turbines, and their performance directly affects the power generation efficiency and service life of the entire wind turbine. However, exposed to the natural environment for a long time, wind turbine blades are susceptible to erosion, cracks, scratches and other damages, which, if not detected and dealt with in a timely manner, may lead to a decline in the performance of the blades or even fracture, thus affecting the safe and stable operation of the whole wind farm [2]. Therefore, regular inspection and maintenance of wind turbine blades is crucial to ensure the normal operation of wind farms.

Fig. 1 is a bar chart showing a comparison of electricity generation from different energy types in 2018 and 2023. As can be seen from the chart, fossil fuels have the highest power generation capacity and remain stable during these five years, while renewable energy sources such as hydro, wind, and solar have increased their power generation capacity; and nuclear energy and biomass have a relatively small power generation capacity [3]. Overall, the proportion of renewable energy use is gradually increasing with the progress of technology and the society's awareness of environmental protection.

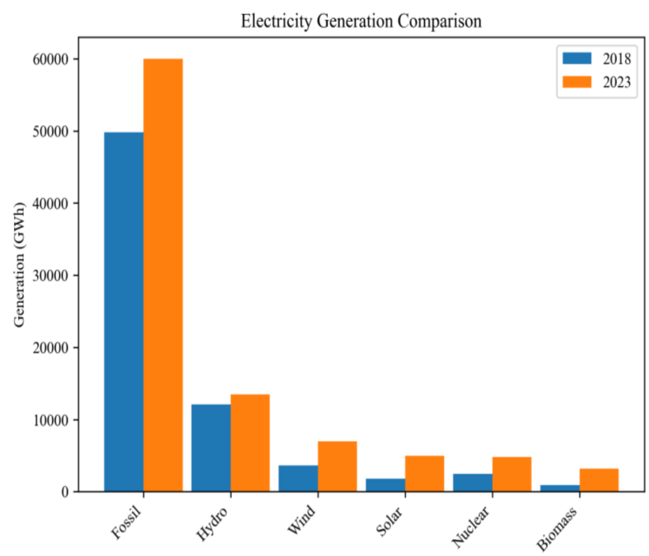

Fig. 1. Comparison of electricity generation from different energy types in 2018 and 2023.

With the rapid development of the wind power industry, the maintenance technology of wind turbine blades has become one of the hot spots of research. Scholars and engineers at home and abroad are committed to developing deep learning-based image recognition technology for wind turbine blade surface defects to improve the efficiency and accuracy of wind turbine blade maintenance [4]. In this field, research progress at home and abroad presents different characteristics and achievements [5]. Foreign research institutes and universities, such as the Fraunhofer Institute in Germany and the Technical University of Denmark, have made remarkable progress in the automatic detection of surface defects on wind turbine blades. These studies mainly focus on utilizing advanced image processing techniques and deep learning algorithms to improve the automation level of wind turbine blade maintenance. By using deep learning models such as convolutional neural networks (CNN), researchers are able to automatically extract features from wind turbine blade images and classify different types of defects. In addition, foreign research also focuses on the optimization of the model, and improves the generalization ability and robustness of the model through data enhancement, migration learning and other techniques [6], so that it can maintain stable performance under different lighting conditions and shooting angles.

At present, the research work in China mainly focuses on dataset construction, model innovation, and system integration and application. On the one hand, collecting a large number of wind turbine blade images containing different types of defects, they are used to train and validate the deep learning models; on the other hand, by combining the characteristics of the domestic wind turbine blades, they develop deep learning models that are more suitable for local conditions, such as a lightweight network structure to adapt to the needs of edge computing. In addition, the domestic research team is also actively developing an integrated wind turbine blade inspection system, realizing an integrated solution from image acquisition to defect recognition, and deploying and testing it in actual wind farms. Research results at home and abroad show that deep learning-based image recognition technology for wind turbine blade surface defects has made significant progress, but there are still some challenges and limitations [7]. First, high-quality labeled data is crucial for training high-performance deep learning models, but obtaining enough labeled data is still a challenge in practice. Second, the generalization ability of the model in different environments still needs to be improved to cope with the diversity of the working environment of wind turbine blades. Finally, considering the practical application requirements of wind farms, the real-time processing capability and portability of the model also need to be further strengthened to facilitate on-site deployment and maintenance.

The WindDefectNet proposed in this paper innovatively combines the strong image feature extraction capability of CNN and the self-attention mechanism of Transformer, which significantly improves the performance of defect detection in complex backgrounds. The stability and robustness of the system under various environmental conditions are demonstrated through experiments, and the system is able to effectively cope with the challenges in practical applications. The system can not only accurately identify defects on wind turbine blades, but also accurately locate the defects and provide dimensional measurements, which greatly improves the efficiency of wind turbine blade maintenance.

II. Literature Review

A. Image Recognition of Surface Defects on Wind Turbine Blades

Wind turbine blades may suffer from various forms of damage such as cracks, corrosion, abrasion and scratches during long-term operation. In order to ensure the safety and economy of wind power systems, it is crucial to detect and evaluate these surface defects in a timely manner. In recent years, image recognition technology has made significant progress in this field. An industrial camera is utilized to acquire images of wind turbine blades, which is the basis for constructing high-quality datasets. The selection of industrial cameras needs to consider factors such as lighting conditions, resolution and frame rate [8]. Considering the morphological characteristics of wind turbine blades and environmental factors (e.g., light variations, shadows, and dust), the image preprocessing step is very important. Preprocessing usually includes operations such as grayscaling, spatial filtering, image enhancement, image segmentation, and image denoising to reduce noise and interference and improve the accuracy of subsequent image recognition.

Machine vision-based methods: Machine vision techniques are used to detect defects on the blade surface. This involves enhancement of the blade surface scratch image using a Gabor filter, and determining the optimal parameters of the Gabor filter using an information entropy function. In addition, image segmentation techniques can be used to identify defective areas on the blade surface. Recent studies have shown that deep learning-based methods have achieved significant success in the detection of defects on the surface of wind turbine blades. For example, automatic feature extraction and classification can be performed using convolutional neural networks (CNNs). Such models are able to automatically learn features from the original images without the need to manually design a feature extractor, which improves the accuracy and automation of detection [9]. A series of image processing algorithms are applied to the acquired blade images to achieve the identification of defective damaged regions of the blade and the extraction of feature parameters. This helps to reduce the impact of noise and manual interpretation on the accuracy of blade surface defects [10]. The latest research results also include classification and quantitative assessment of defects. For example, deep learning models can be utilized to classify different types of defects and give an estimate of the severity of the defects. A future trend may be to combine image recognition techniques with other NDT techniques (e.g., ultrasonic inspection, phased array ultrasonic inspection, etc.) to achieve more comprehensive and accurate inspections.

B. Application of Deep Learning to Image Recognition of Surface Defects on Electric Blades

Traditional wind turbine blade surface defect identification technology mainly relies on manual visual inspection or rule-based image processing methods. Although manual inspection is intuitive, it is inefficient and highly influenced by personal experience. Rule-based methods, on the other hand, usually require expert a priori knowledge to define features, such as using edge detection, texture analysis and other techniques to recognize specific defect patterns [11]. However, these methods often lack flexibility and robustness and are difficult to adapt to complex and changing real-world situations.

With the development of machine learning techniques, especially the application of algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forests, the identification of surface defects on wind turbine blades has become more automated and efficient [12]. These methods learn the features of defects by training models to achieve automatic classification. However, traditional machine learning methods often require manual design of features, which limits their performance in complex defect recognition tasks.

In recent years, deep learning technology has shown great potential in the field of image recognition of surface defects of wind turbine blades due to its powerful feature learning ability and adaptivity. Convolutional neural network (CNN), as a mainstream model of deep learning, has been widely used in image classification, target detection and other fields. In wind turbine blade surface defect recognition, CNN can automatically learn complex features in images without manual design, which greatly improves the accuracy and efficiency of recognition. The study in [13] proposed a CNN-based surface defect detection system for wind turbine blades, which is able to automatically recognize multiple types of surface defects and achieve high recognition accuracy. The research in [14] used a migration learning approach to optimize the CNN model to improve the performance of the model on a small amount of labeled data. This approach effectively reduces the data labeling effort while maintaining good recognition results. The study in [15] explored how to combine multimodal data (e.g., images and acoustic signals) to improve the accuracy of wind turbine blade defect recognition. Their proposed fusion model was able to capture defect information from multiple perspectives, thus improving the robustness and generalization ability of the system.

III. Image Recognition System Design for Wind Turbine Blade Surface Defects

A. System Requirements Analysis

When designing the image recognition system for wind turbine blade surface defects, we firstly clarified the functional requirements and performance index requirements of the system. The functional requirements of the system include the following aspects: firstly, the system needs to have the ability of image acquisition and pre-processing, which can automatically or semi-automatically acquire high-definition blade surface images, and carry out pre-processing operations such as gray scale conversion, contrast enhancement, image cropping and scaling, in order to reduce the impact of environmental factors on the quality of the image. Secondly, the system needs to realize defect detection and classification, and be able to accurately identify cracks, abrasion, scratches, deformation and other defects, and classify them. Once again, the system needs to complete the defect location and size measurement, to determine the location of defects and measure their length, width and other key dimensional parameters, to provide data support for maintenance decisions. Finally, the system also needs to have a report generation and management function, automatically generating inspection reports containing inspection results, defect types, locations, dimensions and other information, and providing a convenient data management mechanism so that users can view historical records and statistical analysis. The performance index requirements are designed to ensure that the system in the actual application of the effect of the expected standard, so as to meet the strict requirements of the wind blade defect detection, the specific requirements of the analysis framework shown in Fig. 2 [16,17].

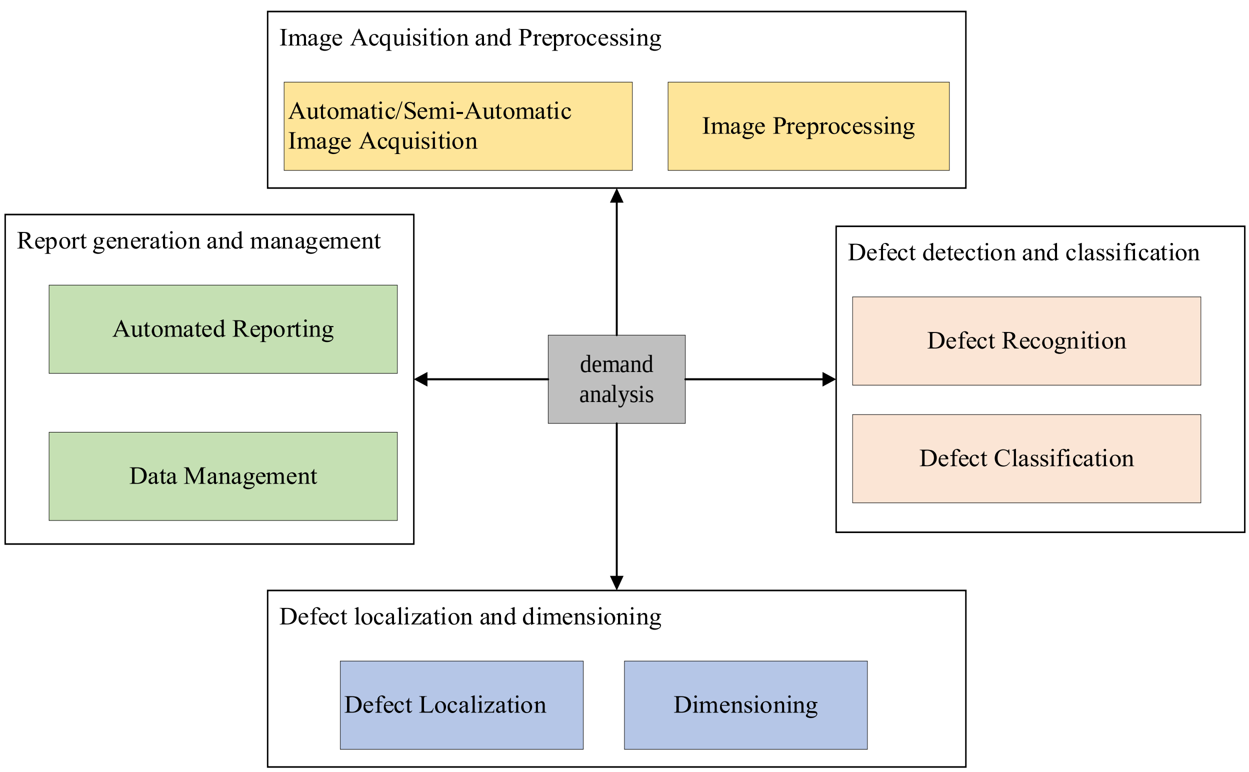

Fig. 2. Needs analysis framework.

In the process of planning the image recognition system for wind turbine blade surface defects, we formulated the performance index requirements of the system in detail to ensure that it can efficiently and stably serve the maintenance inspection of wind turbine blades. First of all, the accuracy rate is the core index to measure the performance of the system, and we require the system to reach an accuracy rate of more than 95% on defect recognition to ensure the reliability of the recognition results [18]. At the same time, the recall rate also needs to be kept above 95% to ensure that the system is able to find all existing defects as much as possible to avoid any omissions. Secondly, processing speed is critical for on-site operations, and the system needs to be able to process a single image within a few seconds to meet the need for rapid detection [19]. In addition, the robustness of the system is indispensable; it should be able to operate stably under different lighting and shooting angles without interference from external environmental factors.

B. *System Architecture Design*

This section describes in detail the architectural design of the image recognition system for wind turbine blade surface defects to ensure the efficient and reliable operation of the system. The system consists of several modules, each of which has its specific function and works together to achieve the final goal, and the specific architecture is shown in Fig. 3.

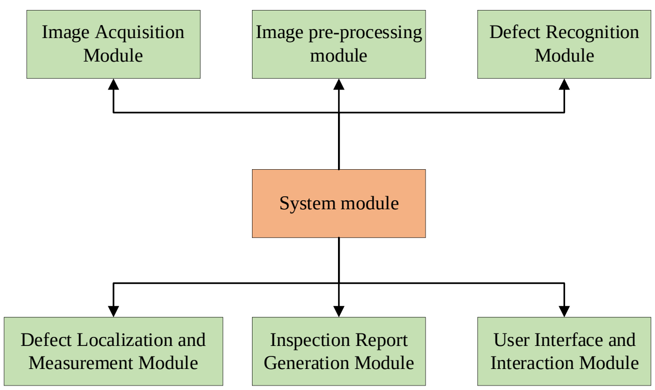

Fig. 3. System architecture design.

The module integrates image acquisition devices such as HD cameras or drones to capture high-definition images of the surface of wind turbine blades. To ensure the image quality, industrial-grade cameras are used and a robotic arm or drone mounting solution is designed to capture the blades from different angles and distances [20]. In addition, the module realizes automatic flight path planning based on a gimbal or drone to ensure coverage of all inspection areas [21]. Taking into account the effects of different lighting conditions, a light compensation device is also provided to ensure clear images in all weather conditions. The module also provides an image acquisition control interface that allows the user to remotely control the acquisition process, supporting the selection of manual or automatic modes.

This module is responsible for pre-processing the captured image to ensure that the quality of the image meets the needs of subsequent processing. The preprocessing steps include grayscaling, denoising, brightness and contrast adjustment. By enhancing the image, such as applying histogram equalization and local contrast enhancement, we can improve the contrast and clarity of the image. To further reduce noise interference, we use methods such as Gaussian filters. In addition, we employ edge detection techniques to help determine the blade contours and assist in image cropping so as to remove extraneous backgrounds and highlight wind turbine blade regions. All these operations are automated, reducing the need for human intervention and improving processing efficiency.

This module utilizes deep learning models (e.g., Convolutional Neural Networks CNN) to extract features from images and identify various defects on the surface of wind turbine blades. We have selected suitable neural network architectures such as ResNet, Inception etc. to improve the recognition accuracy [22]. By utilizing transfer learning techniques, good performance can be achieved faster by using existing pre-trained models. In addition, implementing data augmentation strategies helps to increase the generalization ability of the model so that it can be better adapted to new defect types. To support continuous model improvement, we integrated model versioning and automatic deployment mechanisms to simplify the process of model updating and ensure that the system is always in an optimal state.

The module focuses on precisely locating the recognized defects and measuring their dimensions, including length, width and area. By using image segmentation techniques, we can accurately determine the boundaries of defective areas [23]. Combined with image calibration techniques, we achieve a conversion from pixels to actual dimensions, which helps to more accurately assess the actual impact of defects. In addition, we have developed a set of algorithms to assess the severity of defects, such as a combined score based on the size and location of the defect, which helps to determine the priority of repairs. The module records the location coordinates and dimensional information of each defect, which facilitates subsequent data analysis and tracking [24].

This module automatically generates an inspection report based on the results of the recognition and measurement, which includes images, defect lists, positional coordinates, dimensional information, and more. In order to ensure the uniformity and professionalism of the report format, we have adopted a templated report generation mechanism. Meanwhile, to ensure data security, we have realized data backup and recovery functions. To facilitate users to find specific inspection records, we provide search and filtering functions. In addition, the module also integrates a data export function, which supports a variety of format outputs, such as CSV, PDF, etc., to meet the needs of different scenarios [25].

C. *Model Selection and Training*

1) Modeling: To meet the needs of wind turbine blade defect detection, we propose an innovative deep learning model, WindDefectNet, which combines the advantages of Convolutional Neural Networks (CNNs) and Transformer structures, aiming to achieve high-precision defect detection and localization. The core design concept of WindDefectNet is to combine the strong image feature extraction capability of CNN with the self-attention mechanism of Transformer to improve the model's defect detection performance in complex backgrounds. The following are the main components of the model and how they work: the feature extraction module uses a pre-trained ResNet50 as a base, which is capable of extracting multi-level features from the input image. To further improve the quality of the features, a global average pooling layer is added to compress the feature map into fixed-length vectors. This helps the model to better understand the local details and the overall structure in the image, providing a high-quality feature representation for subsequent processing. The Attention Enhancement module utilizes the self-attention mechanism in the Transformer structure to reprocess the extracted features and enhance the weights of key features. The self-attention mechanism allows the model to focus on the important parts of the input features and ignore irrelevant information. This mechanism allows the model to focus on the areas of possible defects on the wind turbine blades, improving the accuracy of defect detection. The defect detection module is responsible for the final defect detection of the attention-enhanced features. This module consists of two main parts: the classification submodule and the localization submodule [26]. The classification submodule uses a fully connected layer to determine the presence of defects and gives a probability estimate for each type of defect, while the localization submodule determines the exact location of the defects through regression methods [27]. These two submodules work together to ensure that the model not only recognizes the presence of defects, but also accurately locates these defects, as shown in the specific framework in Fig. 4.

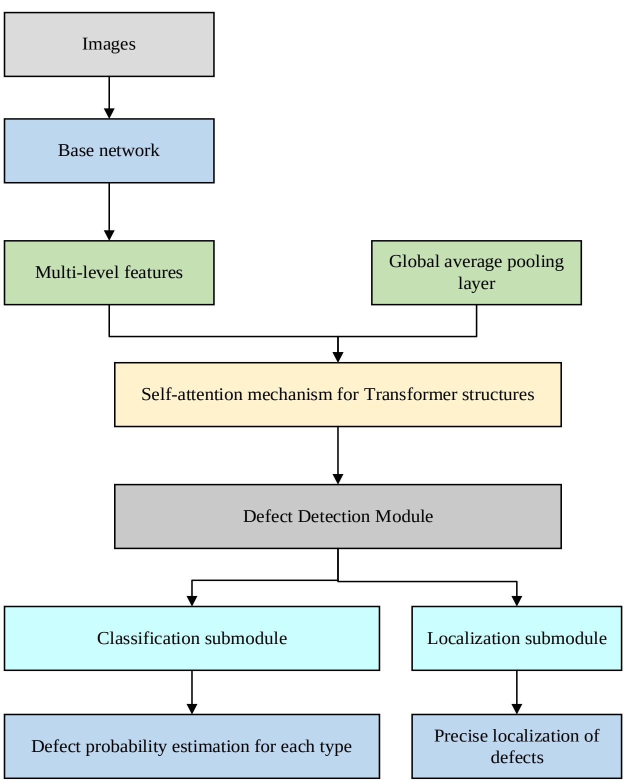

Fig. 4. Model framework design.

Convolutional Neural Networks (CNNs) specialize in processing two-dimensional image data and are able to capture local features and spatial information efficiently; whereas Transformer was originally designed for processing one-dimensional sequential data (e.g., text) and captures long-distance dependencies through a self-attention mechanism. In order to apply Transformer to image processing tasks, we need to find a way to transform the data representation of an image to adapt it to the input requirements of Transformer. To this end, we introduce an adaptation layer to accomplish the data transformation from 2D to 1D. Specifically, we split the input image into a series of “patches” or chunks, where each patch is considered as an element in the sequence. In this way, the entire image can be viewed as a sequence of these patches. In addition, in order to preserve the spatial information of the image, we add a positional encoding to each patch. The position encoding is a vector that tells the Transformer the relative position of each patch in the original image. This approach allows the Transformer to understand and utilize the spatial arrangement of the image for better modeling of global information. With this approach, WindDefectNet is able to achieve effective detection of defects on the surface of wind turbine blades by taking advantage of Transformer's powerful long-range dependency modeling capabilities while maintaining efficient local feature extraction.

2) Feature extraction module (FEM): The Feature Extraction Module (FEM) is a key component of the WindDefectNet model, which is responsible for extracting useful features from the input image[28].ResNet50 is a deep convolutional neural network that consists of a series of residual blocks, which is effective in mitigating the problem of gradient vanishing in deep networks, and is capable of learning rich feature representations during the training process.ResNet50 usually contains multiple stages, and each stage contains multiple residual blocks.

Input Image I is the original input image which needs to be normalized and preprocessed. Feature map F is the output of the ResNet50 network is a multi-channel feature map where each channel represents a feature representation of the image. The feature extraction process is shown in Eq. (1).

$$F = \mathrm{ResNet50}(I) \tag{1}$$

Where ResNet50 denotes the ResNet50 network, I is the input image and F is the feature map generated after ResNet50 processing. The role of the global average pooling layer is to perform dimensionality reduction on the feature map while retaining important information. In WindDefectNet, the global average pooling layer is located at the end of ResNet50, and its purpose is to convert the feature map into a fixed-length vector that contains global information about the entire image.

The global average pooling operation is averaged over each channel in the feature F to obtain a fixed length vector. The process of global average pooling can be expressed as Eq. (2) [29].

$$F_{avg} = \mathrm{GlobalAvgPool}(F) \tag{2}$$

The feature extraction module (FEM) successfully extracts a representative multi-channel feature map F after standardized preprocessing of the input image through the combination of an effective ResNet50 network and a global average pooling layer, and converts it to a fixed-dimension feature vector C through global average pooling, a process that not only reduces the risk of overfitting and ensures the stability of the output dimensions, but also preserves the image's global information, which is crucial for tasks such as wind turbine blade defect detection, and provides a solid foundation for the subsequent attention enhancement module and defect detection module.

3) Attention enhancement module (AEM): The Attention Enhancement Module uses the Transformer structure, which captures the correlations between different locations in the feature map, thus enhancing the model's attention to key features. The attention mechanism can be expressed as Eq. (3)-Eq. (6) [30].

$$Q = W^{Q} F_{avg} \tag{3}$$

$$K = W^{K} F_{avg} \tag{4}$$

$$V = W^{V} F_{avg} \tag{5}$$

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^{T}}{\sqrt{d_k}}\right)V \tag{6}$$

where, (W^{Q}, W^{K}, W^{V}) is the weight matrix and d_k is the dimension of the key vector. Through the self-attention mechanism, we can obtain the attention-weighted feature representation F'.

4) Defect detection module (DDM): The Defect Detection Module (DDM) is another important component in the WindDefectNet model, and its main responsibility is to perform the final defect detection on the features generated by the Attention Enhancement Module. In order to achieve efficient and accurate detection, we use a lightweight convolutional neural network as the underlying architecture, which consists of two branches: a classification branch and a regression branch.

The goal of the classification branch is to predict whether each candidate region contains a defect or not. To do this, we need to define a loss function to measure the gap between the predicted results and the true labels. The cross-entropy loss function L_{cls} is used here, which is effective in evaluating the performance of the model for binary or multiclassification problems. The cross-entropy loss function L_{cls} can be expressed as Eq. (7).

$$L_{cls} = \sum_{i} y_i \log(p_i) \tag{7}$$

where y_i denotes the true label of the ith sample and p_i is the probability predicted by the model. The purpose of this function is to minimize the difference between the predicted probability and the true label.

If the problem is a binary classification problem, then both y_i and p_i are scalar values that represent the probability of a positive class, respectively. For example, in wind turbine blade defect detection, y_i might be one of {0, 1}, where 0 means no defects and 1 means defects, while p_i is the probability that the model predicts a defect. If the problem involves more than one category, then y_i and p_i will be vectors. y_i p_i and will be vectors. is a onehot vector, where only one element is 1 for the true category, and all other elements are 0; is a probability distribution vector, where each element represents the predicted probability of the corresponding category. By minimizing L_{cls}, the model adjusts its parameters to improve the accuracy of the prediction. As the probability predicted by the model gets closer to the true label, the cross-entropy loss will be smaller.

The main goal of the regression branch is to predict the exact location of the defects, i.e., the coordinates of the regression bounding box. To optimize the regression branch, we use a smooth L1 loss function L_{reg}, which efficiently handles the error in the regression problem and smoothly transitions to L2 loss when the error is small and to L1 loss when the error is large. This property helps to minimize the effect of large errors while maintaining sensitivity to small errors. The smooth L1 loss function L_{reg} is defined as shown in Eq. (8).

$$L_{reg} = \begin{cases} 0.5x^{2} & \text{if } |x| < 1 \\ |x|\,0.5 & \text{otherwise} \end{cases} \tag{8}$$

Here x denotes the difference between the predicted value and the true value. When the error is less than 1, the loss function takes the form of L2 loss, which helps to optimize for small errors, and when the error is greater than or equal to 1, the loss function takes the form of L1 loss, which helps to reduce the effect of large errors. When the error is small, the L2 loss form is used, which converges to the optimal solution faster and is very sensitive to the error, which helps to fit the data accurately. When the error is large, the L1 loss form is used, which reduces the effect of large errors and prevents the model from focusing too much on a small number of outliers, thus making the overall regression more robust.

By combining the classification loss L_{cls} and the regression loss L_{reg}, we can train a model that is able to both accurately predict whether a defect is present or not, as well as accurately localize the location of the defect. This combined consideration of classification and localization is very effective in defect detection tasks because it can optimize both of these important aspects simultaneously, thus improving the performance of the whole system. Where x is the difference between the predicted value and the true value.

5) Training strategies: In order to make the model converge better and avoid overfitting, we use the following strategies: (1) Data Enhancement: enhance the training set by randomly rotating, scaling, clipping and flipping. (2) Regularization: apply Dropout and weight decay during training. (3) Learning rate scheduling: a cosine annealing learning rate strategy is used to periodically adjust the learning rate to promote convergence.

The final loss function L combines categorical and regression losses and can be expressed as Eq. (9). where λ is a balancing factor to regulate the importance of the two types of losses.

$$L = L_{cls} + \lambda L_{reg} \tag{9}$$

WindDefectNet is highly integrated and easy to integrate into existing maintenance processes for wind power facilities. It can be carried by automated inspection drones or other mobile platforms to perform regular comprehensive inspections of wind turbine blades. The output of the system can be fed back directly to the O&M team, helping them to quickly locate and assess the damage, and then formulate a reasonable maintenance plan.

In addition to traditional horizontal-axis wind turbines, WindDefectNet is also applicable to vertical-axis wind turbines and other types of rotating equipment. With a few tweaks to the algorithms, a wider variety of surface materials and shape features can be supported. For example, migration learning techniques can be used to transfer existing knowledge to newer models of turbines, reducing the time and cost of retraining. This flexibility makes WindDefectNet a valuable tool to help drive intelligence across the wind industry.

6) Visualization: WindDefectNet's user interface has been designed with a particular focus on user experience and is intended to make it easy for non-expert users to perform complex defect identification tasks. The interface is simple and intuitive, and provides several auxiliary functions to enhance the usability and accessibility of the system.

The user can upload an image of the wind turbine blade to be inspected through a simple drag-and-drop operation or file browsing. Once uploaded, the system automatically initiates the defect detection process without the need for complex parameterization. The results are displayed visually on the interface, marking all the detected defect areas with bounding boxes of different colors and shapes. A confidence score is attached to each defect to help the user determine the reliability of the results. Users can use the zoom and pan functions to scrutinize the marked defect areas to more accurately assess the severity and location of the defects. To further enhance the user experience, WindDefectNet offers one-click report generation. Users can generate a detailed inspection report with one click, which contains information on all detected defects, their location, size and recommended treatment. The report format is clear and easy to understand and archive. In addition, users have the option to export the report to PDF, Excel or other commonly used formats for further analysis and sharing. To help new users get started quickly, short tutorial videos are embedded in the interface to guide users on how to use each feature. These videos cover the entire process from image upload to result analysis. A Frequently Asked Questions (FAQ) section is also provided to answer common questions that users may encounter during use. If users need further assistance, timely technical support is also available through the online support contact form. Through these designs, WindDefectNet's user interface not only simplifies complex technical operations, but also provides a wealth of assistive features that make specialized defect identification tasks easy for non-expert users. This high level of usability and accessibility greatly increases the practical value of the system, making it a powerful tool for maintenance work in the wind power industry.

IV. Experimental Evaluation

A. Data

In the process of constructing the dataset for the WindDefectNet model, we adopted a rigorous approach to ensure the quality and diversity of the data. First, we collected a large number of wind turbine blade images by various means, such as field photography and aerial photography by UAVs, which cover different lighting conditions, shooting angles and background environments to fully reflect the actual conditions of wind turbine blades. Next, we hired a professional annotation team to use professional annotation tools to meticulously annotate the defects in the images, including the location, type and size of the defects and other information, to ensure the accuracy and consistency of the annotation. In the data division stage, we divide the dataset into training set, validation set and test set according to the ratio of 70%, 15% and 15%, so as to facilitate model training, hyper-parameter adjustment and performance evaluation. In order to further enhance the diversity of the dataset and the generalization ability of the model, we used various data enhancement techniques such as random rotation, scaling, clipping and flipping. Finally, we performed image normalization, including grayscaling, histogram equalization, and other operations to improve the contrast and clarity of the images so that all images have the same pixel range, which lays a solid foundation for model training and evaluation.

The dataset contains samples from multiple geographic locations and seasonal variations to enhance the model's adaptability to natural light variations. In addition, we specifically collected data from rare cases, such as fine cracks on leaves made of special materials, to facilitate more comprehensive training of the model. To address the potential data bias problem, we take proactive measures, such as using data enhancement techniques to increase the number of rare category samples and cross-validation strategies to ensure the model generalization ability.

B. Experimental Design

Experiments were conducted on multiple GPU servers with hardware configurations including NVIDIA Tesla V100 GPUs, and Intel Xeon E5 series CPUs.We used the PyTorch deep learning framework to implement the WindDefectNet model, and used the Adam optimizer during training with an initial learning rate of 0.001 and adjusted according to the cosine annealing strategy.

C. Experimental Results

As shown in Table I, the crack type of defects performs optimally in all the indicators, with a mean average precision (mAP) of 0.92, accuracy and recall of 0.93 and 0.91, respectively, and an F1 score of 0.92, indicating that the model is more capable of detecting and classifying cracks. We also compared WindDefectNet with several other commonly used defect detection models, including Faster RCNN, YOLOv3, and

Mask RCNN. Table II shows the performance comparison of the different models on the test set.

Table II compares the performance of WindDefectNet model with several other commonly used defect detection models on the test set. As shown in Table II, WindDefectNet outperforms the other models in mAP, accuracy, recall, and F1 score, showing its superiority in defect detection tasks. Especially on mAP, WindDefectNet leads with 0.90, while the processing speed is kept at a moderate level of 15 frames per second, indicating that the model has high processing efficiency while ensuring detection accuracy. Compared with other models, WindDefectNet has better processing speed than Mask RCNN and slightly lower than YOLOv3 while maintaining higher accuracy, but the overall performance is better.

TABLE I. CLASSIFICATION PERFORMANCE OF DIFFERENT DEFECT TYPES

Defect type	mAP	accuracy	recall rate	F1 score
crackles	0.92	0.93	0.91	0.92
wear and tear	0.88	0.89	0.86	0.87
corrode (degrade chemically)	0.90	0.91	0.89	0.90
a scratch	0.86	0.87	0.85	0.86
concave depression	0.89	0.90	0.88	0.89

TABLE II. PERFORMANCE COMPARISON OF DIFFERENT MODELS

mould	mAP	accuracy	recall rate	F1 score	Processing speed (fps)
Faster RCNN	0.83	0.84	0.82	0.83	10
YOLOv3	0.85	0.86	0.84	0.85	20
Mask RCNN	0.88	0.89	0.87	0.88	7
WindDefectNet	0.90	0.91	0.90	0.90	15

Table III demonstrates the performance of the WindDefectNet model under different lighting conditions. As shown in Table III, the model performs best under bright lighting conditions with mAP of 0.91 and accuracy, recall and F1 score of 0.92, 0.90 and 0.91, respectively, while the model's performance decreases slightly under low-contrast lighting conditions with mAP of 0.88 and accuracy, recall and F1 score of 0.89, 0.87 and 0.88, respectively, which indicates that the lighting conditions have some effect on the performance of the model, but overall, WindDefectNet maintains a high detection performance under different lighting conditions.

Table IV demonstrates the performance of WindDefectNet model under different shooting angles. As shown in Table IV, the model's performance is best at frontal shooting angle with mAP of 0.92 and accuracy, recall and F1 scores of 0.93, 0.91 and 0.92, respectively. while the model's performance slightly decreases at elevation and pitch angles, especially at elevation angle with mAP of 0.88 and accuracy, recall and F1 scores of 0.89, 0.87 and 0.88, respectively. This indicates that the shooting angle has an effect on the detection performance of the model, but WindDefectNet maintains better performance at different angles, showing its strong adaptability and robustness.

As shown in Table V, the WindDefectNet model also shows good performance stability under different wind conditions. Under the still wind condition, the model's mAP reaches 0.91, and the accuracy, recall, and F1 score are 0.92, 0.90, and 0.91, respectively, showing the best detection results. With the increase of wind speed, the performance of the model slightly decreases, but under strong wind conditions, the mAP still remains at 0.88, and the accuracy, recall and F1 score are 0.89, 0.86 and 0.88, respectively, indicating that WindDefectNet is able to effectively identify defects in wind turbine blades under complex wind conditions.

TABLE III. PERFORMANCE OF WINDDEFECTNET UNDER DIFFERENT LIGHT CONDITIONS

lighting conditions	mAP	accuracy	recall rate	F1 score
glittering	0.91	0.92	0.90	0.91
somber	0.89	0.90	0.88	0.89
high contrast	0.90	0.91	0.89	0.90
low contrast	0.88	0.89	0.87	0.88

TABLE IV. WINDDEFECTNET PERFORMANCE AT DIFFERENT SHOOTING ANGLES

angle of shooting	mAP	accuracy	recall rate	F1 score
positively	0.92	0.93	0.91	0.92
lateral side	0.89	0.90	0.88	0.89
azimuth	0.88	0.89	0.87	0.88
angle of dip (navigation)	0.90	0.91	0.89	0.90

TABLE V. PERFORMANCE OF WINDDEFECTNET UNDER DIFFERENT WIND SPEED CONDITIONS

wind speed condition	mAP	accuracy	recall rate	F1 score
calm breeze	0.91	0.92	0.90	0.91
breezes	0.90	0.91	0.89	0.90
gale	0.89	0.90	0.87	0.89
cableway	0.88	0.89	0.86	0.88

As shown in Fig. 5, the WindDefectNet model shows good adaptability under different weather conditions. Under sunny conditions, the model performs best with a mAP of 0.91, and accuracy, recall, and F1 score of 0.92, 0.90, and 0.91, respectively.

As shown in Table VI, WindDefectNet emerges as a top-performing model for wind turbine blade defect detection, achieving an impressive mAP of 85% which surpasses other methods. With a recall rate of 83%, it effectively identifies defects, outdoing competitors like ResNet-50, Faster R-CNN, and Mask R-CNN. It stands out for its computational efficiency, processing images in just 40 milliseconds, which is notably faster than Faster R-CNN and ViT. Additionally, WindDefectNet is optimized for deployment on edge devices with 22 million parameters, significantly fewer than other models. Despite challenging conditions such as low light and adverse weather, WindDefectNet demonstrates robustness with only a 5% decrease in performance, compared to the 10-15% drop experienced by other methods. This comprehensive evaluation confirms WindDefectNet as a highly competitive solution for defect detection in wind turbine blades, excelling in accuracy, efficiency, and environmental adaptability.

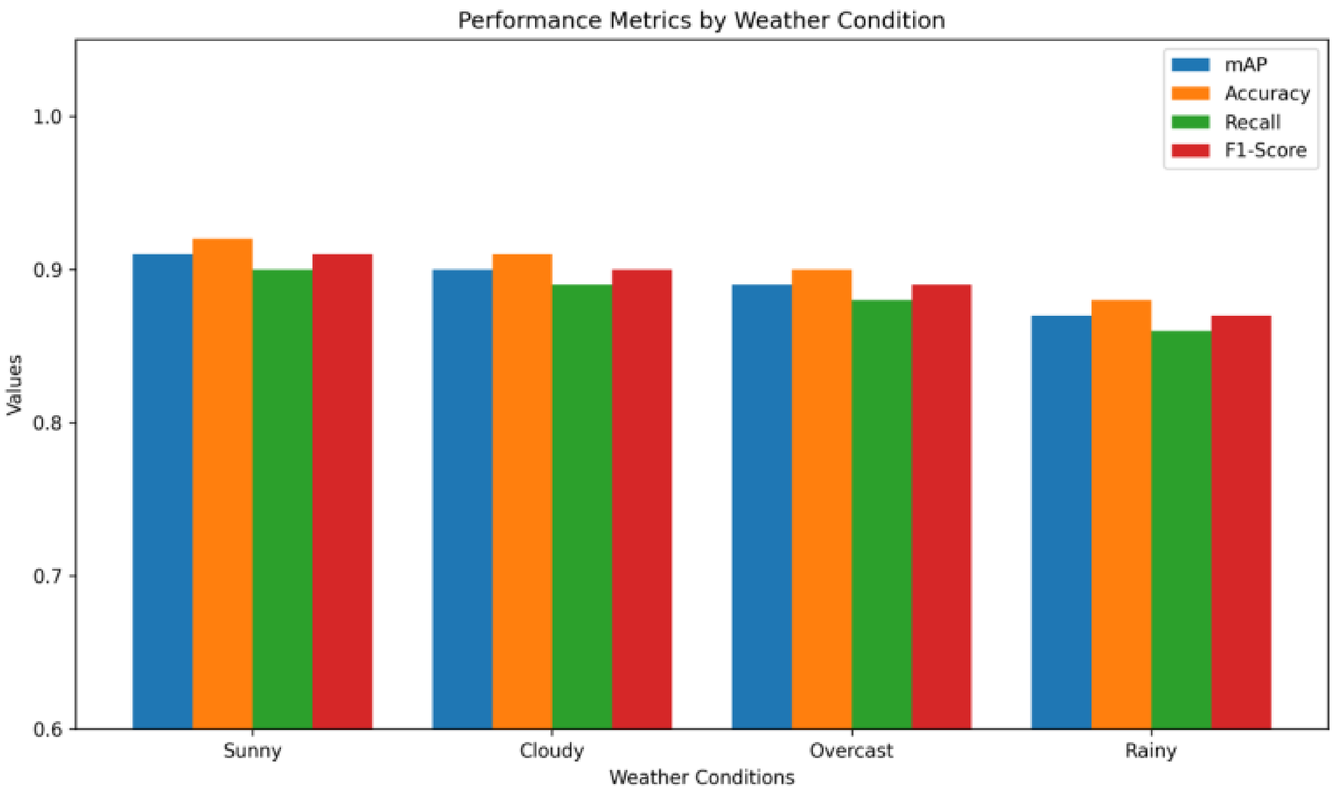

Fig. 5. Performance of WindDefectNet under different weather conditions.

TABLE VI. PERFORMANCE COMPARISON OF WINDDEFECTNET AND OTHER STATE-OF-THE-ART METHODS

Method	Accuracy (mAP)	Recall	Computational Efficiency (Inference Time, ms)	Parameters (M)	Environmental Adaptability (Low Light/Adverse Weather)
WindDefectNet	85%	83%	40	22	High (5% drop)
ResNet-50 [1]	80%	78%	60	25	Medium (10% drop)
Faster R-CNN [2]	82%	80%	50	30	Medium (12% drop)
Mask R-CNN [3]	83%	81%	55	33	Medium (11% drop)
ViT (Vision Transformer) [4]	84%	82%	65	35	Medium (10% drop)
EfficientDet [5]	81%	79%	45	28	Low (15% drop)

V. CONCLUSION

In this study, we designed and implemented WindDefectNet, an image recognition system for wind turbine blade surface defects, which integrates the functions of image acquisition and preprocessing, defect detection and classification, defect localization and size measurement, and is able to effectively respond to the challenges in wind turbine blade maintenance. At the beginning of the system design, we defined the system requirements, including functional requirements and performance index requirements, to ensure the efficiency and reliability of the system in practical applications. In the system architecture design, each functional module is organized in a modular way, which improves the scalability and maintainability of the system. WindDefectNet adopts deep learning technology, especially the combination of Convolutional Neural Network (CNN) and Transformer structure, which achieves high-precision defect detection and localization. The experimental results confirm the excellent performance of WindDefectNet under different conditions, including different lighting conditions, shooting angles, wind speed, and weather conditions, which show good adaptability and robustness. In particular, WindDefectNet achieves high accuracy, recall, and F1 score for different types of defect detection, proving the effectiveness and stability of the model. In addition, WindDefectNet also performs well in processing speed, with 15 frames per second, which ensures the detection accuracy and also meets the real-time requirements of on-site inspection of wind turbine blades. Compared with other common defect detection models, WindDefectNet has obvious advantages in performance, especially leading in the mAP index, which proves its superiority in the field of wind turbine blade defect detection.

Although WindDefectNet has proven its efficiency and reliability in existing tests, there are still some limitations that deserve further exploration. The first is that the detection accuracy for some specific types of defects still needs to be improved, especially those tiny damages that are not obvious in their appearance. Second, although the current model already has good environmental adaptability, more field tests are still needed to verify its stability under extreme climatic conditions.

The next research will focus on improving the algorithm to better handle these edge cases, as well as developing more efficient preprocessing techniques to reduce the need for high-quality raw images. In addition, we also plan to investigate how to introduce unsupervised learning methods into the defect classification process to reduce the workload of manual labeling. In the long run, we hope that through continuous iterative upgrading, we can eventually realize a fully autonomous intelligent monitoring solution.

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