International Core Journal of Engineering Volume 12 Issue 3, 2026
ISSN: 2414-1895 DOI: 10.6919/ICJE.202603_12(3).0027

Wind Turbine Blade Defect Detection Method based on Improved YOLOv11

Xinyue Hu, Yizhen Lu, Shuya Ye, Wei Luo, Na Li*

School of Information Science and Engineering, Xinjiang University of Science and Technology, Korla, Bayingolin Mongolian Autonomous Prefecture, Xinjiang Uygur Autonomous Region, China

*Corresponding author: Na Li

Abstract

Aiming at the problems of low efficiency of manual inspection, easy missed detection of small target defects, and severe interference from complex backgrounds in wind turbine blade defect detection for wind power operation and maintenance scenarios, an improved YOLOv11 model integrating feature enhancement and dynamic sample optimization is proposed. Firstly, the local perception unit of images is constructed through superpixel texture analysis, and the texture entropy of each region is quantified combined with the Gray Level Co-occurrence Matrix (GLCM) to realize the adaptive localization of potential defect regions of blades. Secondly, the Coordinate Attention (CA) module is embedded in the backbone network to dynamically generate spatial weight masks, which strengthens the network's focusing ability on high-entropy defect regions and suppresses the artifact interference caused by complex blade textures and field environments. Meanwhile, the weighted Bidirectional Feature Pyramid Network (BiFPN) is designed to replace the original multi-scale fusion structure, which optimizes the feature aggregation process and enhances the edge consistency representation of small-sized defects. In addition, the detector head structure is optimized and the Intersection over Union (IoU) loss function is introduced. Combined with the multi-category focal loss, the penalty coefficient for easy and hard samples is dynamically adjusted according to the distribution of training samples, which alleviates the model bias caused by the long-tail distribution of industrial data and category imbalance. Experimental results show that compared with the original model and mainstream detection models such as Faster-RCNN, SSD and YOLO series, this method achieves better performance in detection speed and accuracy, and effectively improves the detection performance of the system in complex scenarios such as noise interference and low illumination.

Keywords

Wind Turbine Blade; Defect Detection; YOLOv11; Feature Fusion; Attention Mechanism.

1. Introduction

Against the backdrop of the global energy structure transformation, wind power generation has become a core clean energy form for achieving the "dual carbon" goals. As the key component of wind turbines for capturing wind energy, the health state of wind turbine blades directly determines the power generation efficiency and operational safety of the units. Blades operate in complex field environments for a long time and are subject to airflow impact, sand wear, ultraviolet radiation and other factors, which easily lead to cracks, corrosion, surface spalling and other defects[1]. These defects are tiny in scale and randomly distributed in the initial stage; if not detected and repaired in a timely manner, they will cause serious accidents such as blade fracture and unit shutdown. Therefore, wind turbine blade defect detection is of great significance for the intelligent operation and maintenance of the wind power industry[2].

Traditional wind turbine blade defect detection methods include manual climbing inspection, manual interpretation of UAV aerial photography, and acoustic emission detection. These methods require professional equipment and operators, suffering from low detection efficiency, large subjective errors, high on-site safety risks, and thus cannot meet the demand for large-scale intelligent operation and maintenance in the modern wind power industry. In recent years, deep learning methods based on machine vision have been widely applied in the field of industrial defect detection[3]. Models such as SSD, YOLO series and Faster RCNN have realized a certain degree of intelligent detection. However, in the wind turbine blade detection scenario, affected by uneven illumination, complex surface textures, large differences in defect scales and other factors, existing models still have problems such as missed detection of small target defects, misdetection and insufficient positioning accuracy[4].

To address the above problems, this paper proposes an improved YOLOv11 algorithm for wind turbine blade defect detection. The Simple Linear Iterative Clustering (SLIC) superpixel segmentation and GLCM analysis are used to capture fine-grained local defect information of blades. The CA module is embedded and the BiFPN feature fusion structure is optimized to enhance the model's ability to extract features of small target defects[5]. A wind turbine blade-specific data augmentation strategy is designed, combined with the multi-category focal loss function to solve the problems of small samples and category imbalance in training samples, thus improving the detection accuracy and robustness of the algorithm in complex scenarios.

2. Principle and Implementation of the Detection Algorithm

The overall process of the wind turbine blade defect detection algorithm in this paper is as follows: first, the SLIC superpixel segmentation and GLCM texture analysis are used to locate the potential defect regions of blade images; then the preprocessed images are input into the improved YOLOv11 model to complete feature extraction and multi-scale fusion; finally, the optimized detector head outputs the defect detection results. Meanwhile, the model optimization training is completed combined with the specific data augmentation strategy and multi-stage training strategy.

2.1 Blade Image Texture Analysis and Data Augmentation

This module realizes the adaptive localization of potential defect regions of blades through superpixel segmentation, and designs a wind turbine blade-specific data augmentation strategy to expand sample diversity and alleviate the problems of small samples and category imbalance in industrial scenarios.

2.1.1 Superpixel Segmentation and Texture Feature Analysis

The algorithm realizes SLIC superpixel segmentation based on the local K-means clustering method. First, the RGB blade images are converted to the CIE-LAB color space to separate the brightness and color channels, thus reducing the interference of illumination changes and complex backgrounds. Then the number of superpixel seed points is determined and the image grid is initialized; the initial clustering centers are optimized to the position with the minimum gradient value to avoid selection at the image edge or noise points. In the 2S×2S region of each clustering center, the comprehensive similarity between pixel points and clustering centers is calculated through color similarity and spatial distance similarity to complete pixel clustering, and the clustering centers are updated iteratively until convergence.

After superpixel segmentation, the entropy value of each superpixel is calculated by GLCM to describe the regional texture features. A larger entropy value indicates a more unbalanced gray distribution and more complex texture in the region, meaning a higher probability of blade defect regions. An entropy threshold is set, and the superpixels with entropy values higher than the threshold are classified as high potential defect regions. The subsequent attention module guides the model to focus on such regions, improving the pertinence of defect detection.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202603_12(3).0027

2.1.2 Wind Turbine Blade-Specific Data Augmentation Strategy

Aiming at the characteristics of small samples, category imbalance and high proportion of small targets in wind turbine blade defect data, a multi-dimensional blade-specific data augmentation strategy is designed. Geometric transformations such as random rotation and affine transformation are adopted to expand samples. Training images containing small defects (the relative area of the annotation box < 0.01) are assigned a sampling weight of 2~3 times to increase the training frequency of small target samples. In addition, new defect samples are generated through DCGAN generation and defect pasting to further expand the scale of the training set and alleviate the problem of category imbalance.

2.2 Improved YOLOv11 Model

The improved YOLOv11 network structure consists of four parts: input end, backbone network, neck network and head module.

The input end performs offline data augmentation on the input images, combining the Mosaic operation with the wind turbine blade-specific data augmentation strategy to increase data diversity and improve the generalization ability of the model, which helps the model identify small-scale defect targets.

The backbone network is responsible for feature extraction. On the basis of the original YOLOv11 backbone network, the CA module is embedded into the C2f module to construct the C2f-CA module, which replaces the original C2f module. The convolution module reduces the model complexity by splitting channels and changing the spatial resolution of feature maps, and the dense residual structure improves parameter sharing and gradient flow. While retaining the original gradient branches, the C2f-CA module captures the spatial position feature dependence through the coordinate attention mechanism to strengthen the feature expression of defect regions. The SPPF module expands the receptive field, maintains the translation invariance of features and improves the training effect of deep networks.

The neck network is the intermediate layer connecting the backbone network and the detector head. The weighted BiFPN is designed to replace the original PANet structure. Through the top-down and bottom-up bidirectional information flow, the fusion of high-level semantic information and low-level spatial positioning information is realized. Meanwhile, skip connections between peer input and output nodes are added to improve the multi-scale feature integration ability and optimize the feature fusion effect of small target defects.

The head module adopts a decoupled design, which separates the classification and positioning tasks to eliminate the mutual interference between tasks and improve the positioning and classification accuracy of the model for defect targets.

2.3 Coordinate Attention Mechanism Module

In wind turbine blade defect detection, conventional networks tend to waste computing resources on non-target background regions, resulting in insufficient ability to extract features of tiny defects. In this paper, the CA module is embedded in the backbone network to help the model reasonably allocate the feature attention weight and highlight the feature expression of small target defects.

The CA module breaks through the limitation of traditional channel attention that ignores position information, and decomposes channel attention into two one-dimensional feature encoding processes in horizontal and vertical directions to capture the spatial position dependence in different directions. The module receives high-resolution shallow features and low-resolution deep features, extracts global features through adaptive average pooling, learns feature weights through convolution operation, generates attention weights in horizontal and vertical directions and maps them to the original feature map, thus realizing the feature enhancement of defect regions and the feature suppression of background regions. At the same time, the CA module realizes the cross-scale aggregation of features with different resolutions, improves the model's ability to perceive global

ISSN: 2414-1895 DOI: 10.6919/ICJE.202603_12(3).0027

context, makes the model focus on defect regions, and thus improves the detection and positioning performance.

2.4 Optimized BiFPN Feature Fusion Structure

Aiming at the problem of easy dilution of small target features in traditional BiFPN for wind turbine blade detection, this paper optimizes the BiFPN structure: skip connections between peer input and output nodes are added in the bidirectional fusion path to promote the transfer of fine-grained features at the same scale level, effectively capture local detail information, reduce the gradient vanishing problem and improve the network's feature learning and transfer ability. In view of the characteristic that small blade defects are concentrated in the high-resolution feature layer, the P3 layer of BiFPN is additionally strengthened by adding two convolution layers and BatchNorm layers to retain more detail features of small targets and avoid feature dilution.

The feature fusion of the optimized BiFPN assigns weights to different input features through learnable weights to realize adaptive feature fusion. Taking the feature layer P_4 as an example, the intermediate feature P_4^{td} and the output feature P_4^{out} are obtained by weighted fusion of multi-scale features and convolution operation, which effectively integrates the semantic and detail information of adjacent layers and improves the model's ability to understand the features of defects of different scales.

2.5 Optimized Detector Head and Loss Function

The training dataset of wind turbine blade defects has an obvious category imbalance problem, which easily leads to insufficient model learning of difficult-to-detect and small-sample defects. To address this problem, this paper optimizes the detector head structure and designs a multi-loss fusion loss function system.

The IoU loss function is adopted to optimize the bounding box regression, which calculates the loss directly based on the overlapping area of bounding boxes to improve the positioning accuracy of defect targets. The IoU loss function is defined as: $L_{IoU}=1-IoU$, where IoU is the ratio of the intersection area to the union area of the predicted bounding box and the real bounding box.

On this basis, a multi-category focal loss function is introduced to dynamically adjust the penalty coefficient for easy and hard samples according to the distribution of training samples, making the loss function focus more on the less numerous defect categories and difficult-to-detect samples. The formula is: $FL(p_t)=-(1-p_t)^{\gamma}\log(p_t)$, where p_t is the probability score predicted by the model, and γ is the focal parameter; increasing γ can improve the attention to difficult-to-classify samples.

The final total loss function is composed of the weighted classification loss and bounding box regression loss. The loss contribution of different tasks is balanced through hyperparameters, which effectively alleviates the category imbalance problem and improves the comprehensive detection performance of the model.

3. Experimental Design and Result Analysis

3.1 Experimental Dataset

The experimental dataset is collected by UAV on-site aerial photography and laboratory simulated damage, which is consistent with the actual inspection scenario of wind farms. It includes a total of 3000 valid images, containing 1200 crack samples, 800 corrosion samples, 600 surface spalling samples and 400 defect-free background samples, covering common defect types of wind turbine blades. LabelStudio is used to complete the bounding box annotation with the format of (x,y,w,h,cls). The dataset is divided into a training set (2400 images), a validation set (300 images) and a test set (300 images) at a ratio of 8:1:1. Images with rotation, noise processing and overlapping targets are added to improve the robustness of the model. Small defects (relative area < 0.01) account for 45% of the dataset, which is consistent with the actual industrial detection scenario.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202603_12(3).0027

The experimental hardware environment is Intel Core i9-12900K CPU, NVIDIA RTX 3090 GPU (24G video memory) and 32G DDR5 memory. The software environment is Ubuntu 20.04 operating system, Python 3.9, PyTorch 2.1, Ultralytics 8.1 and OpenCV 4.8. In the experiment, the proposed algorithm is compared with the original YOLOv11 and mainstream models such as Faster-RCNN, SSD and YOLOv5s, with unified experimental environment, parameters, input and output to eliminate random errors.

3.2 Ablation Experiment

To verify the influence of each improved module on detection performance, an ablation experiment is carried out, and the algorithm performance is evaluated from four indicators: Precision (P), Recall (R), mAP@0.5 and mAP@0.5:0.95. The results are shown in Table 1.

Table 1. Comparison of ablation experiment results

Group	BiFPN	Coordinate Attention	Specific Data Augmentation	Precision	Recall	mAP@0.5	mAP@0.5:0.95
1	Not adopted	Not adopted	Not adopted	0.875	0.824	0.814	0.482
2	Adopted	Not adopted	Not adopted	0.886	0.857	0.853	0.501
3	Not adopted	Adopted	Not adopted	0.883	0.851	0.842	0.495
4	Not adopted	Not adopted	Adopted	0.881	0.845	0.836	0.492
5	Adopted	Adopted	Adopted	0.902	0.895	0.897	0.534

It can be seen from Table 1 that all improved modules can improve the detection performance of the original model. After adding BiFPN alone, the Recall and mAP@0.5 are increased by 3.3% and 3.9% respectively, which enhances the model's ability to extract features of small-scale targets. The coordinate attention module increases the Recall by 2.7% and mAP@0.5 by 2.8 percentage points, which effectively alleviates the interference of complex backgrounds and improves the ability to identify tiny defects. The specific data augmentation strategy expands the sample diversity and improves the problems of small samples and category imbalance. When all improved modules are added at the same time, the model achieves the optimal comprehensive performance: the Precision is increased by 2.7%, the Recall by 7.1% and the mAP@0.5 by 8.3 percentage points, and the ability of defect feature extraction and recognition is significantly enhanced.

3.3 Model Training

All models are trained from scratch with a three-stage training strategy. The initial learning rate is set to 0.005, and the learning rate is dynamically adjusted by cosine annealing. The batch size is set to 16, and the total training epochs are 300. The SGD optimizer is adopted with a momentum of 0.937 and a weight decay coefficient of 0.0005. The loss weight of small target defects is set to 2.0 to balance the training priority of different types of samples.

During the model training process, the loss curve of the improved YOLOv11 model converges faster than that of the original model. The loss values of the two models are close when trained to about 100 epochs, and then the loss value of the original model tends to be stable, while the loss value of the improved model continues to decline and finally remains at a lower level. This proves that the model improvement and parameter setting in this paper are more reasonable, and the model can locate and identify blade defects more accurately.

3.4 Visual Analysis of Results before and after Improvement

Visual comparison is carried out for complex scenarios of blade defect detection (target overlap, low illumination, reflection interference, etc.). The results show that the original model is prone to miss tiny cracks, low-contrast defects in dark areas and small-sized defects during detection, and even cannot identify defects in the reflection interference scenario. In contrast, the improved model can successfully detect various defects in the above complex scenarios, extract more features in low-texture and repeated texture regions, and has a stronger ability to identify small targets and low-contrast defects. At the same time, it can effectively suppress the interference of reflection artifacts and improve the detection performance in complex scenarios.

3.5 Algorithm Comparison Experiment

The proposed method is compared with mainstream models such as Faster-RCNN, SSD, YOLOv5s and the original YOLOv11, with a unified input image size of 640×640 and model hyperparameters. The test results are shown in Table 2.

Table 2. Comparison of evaluation scores of different algorithms

Algorithm Model	Precision	Recall	mAP@0.5	mAP@0.5:0.95	FPS (Frames Per Second)
Faster-RCNN	0.805	0.782	0.821	0.415	12
SSD	0.738	0.756	0.748	0.378	65
YOLOv5s	0.872	0.831	0.892	0.506	58
Original YOLOv11	0.875	0.824	0.814	0.482	55
Proposed method	0.902	0.895	0.897	0.534	52

The experimental results show that the improved model in this paper is superior to other mainstream models in Precision, Recall and mean Average Precision, while maintaining an excellent inference speed. Compared with SSD, the Precision and Recall are increased by 16.4% and 13.9% respectively; compared with YOLOv5s, the Precision is increased by 3.0%, the Recall and mAP@0.5 by 6.4% and 0.5 percentage points respectively; compared with the original YOLOv11, the Precision is increased by 2.7% and the mAP@0.5 by 8.3 percentage points. The inference speed of the proposed model is 52 FPS, which can meet the demand for industrial real-time detection. It achieves a good balance between detection accuracy and speed, and is more suitable for wind turbine blade defect detection in wind power operation and maintenance scenarios.

4. Conclusion

In wind turbine blade defect detection, the traditional YOLOv11 model has problems such as missed detection of small target defects and insufficient robustness in complex scenarios due to the influence of illumination, complex backgrounds, surface textures and defect scales. To address these problems, this paper proposes an improved YOLOv11 method for wind turbine blade defect detection. The SLIC superpixel segmentation and GLCM texture analysis are used to locate potential defect regions, guiding the model to focus on regions with high defect probability. The CA module is embedded in the backbone network to strengthen the feature expression of defect regions and suppress background interference. The BiFPN feature fusion structure is optimized to improve the model's ability to fuse and extract features of small target defects. A wind turbine blade-specific data augmentation strategy is designed, combined with the IoU loss and multi-category focal loss to alleviate the problems of small samples and category imbalance, thus improving the detection accuracy of the model.

Experimental results show that compared with mainstream algorithms such as Faster-RCNN, SSD and the original YOLOv11, the proposed method has better performance in both detection accuracy and speed, and effectively improves the wind turbine blade defect detection performance in complex scenarios such as noise interference and low illumination, providing technical support for the intelligent operation and maintenance of the wind power industry.

Future research will focus on the engineering implementation and performance optimization of this method: a hybrid detection model will be constructed combined with the Transformer architecture to improve the detection ability of large-area cross-scale cracks; multi-modal data fusion technology will be introduced, combining infrared thermal imaging and visible light images to improve the adaptability of the model in complex weather such as night and rainy days; research on model lightweight will be carried out, and a lightweight model adapted to UAV on-board platforms will be constructed through pruning, quantization, knowledge distillation and other technologies to realize on-site real-time online detection of wind turbine blades.

Acknowledgments

Fund Project: Research on Adaptive Recognition Method for UAV Inspection of Wind Turbine Blades in High-Temperature and Sandy Dust Environment (University-Level Project, No.2025-KYPT33, 2025.07-2026.07).

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