A Method for Identifying Small-Size Defects of Insulators in Transmission Lines Based on the COK-YOLO Algorithm

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Abstract. Insulators are an important guarantee for maintaining the stable operation of the power system. The faults caused by insulator defects will endanger the operation safety of the power system and may even lead to the breakdown of the system. Currently, there are various methods for detecting insulator damage. However, it is difficult for all the existing algorithms to detect the problem of small insulator defects. Aiming at the problem that small insulator defects are difficult to detect, this paper proposes a method for detecting small insulator defects based on the improved YOLOv8. This paper draws on the principle of Cross Stage Partial Network to put forward the COK-YOLO algorithm, and uses the Omni kernel to achieve multi-scale feature extraction, which improves the detection ability of small insulator defects and finally enhances the detection results of various types of defects including breakage and pollution flashover. The experimental results show that the improved algorithm strengthens the detection ability of small insulator defects and provides a guarantee for the safe operation of the power system.

Keywords: Insulator Defects, Defect Detection, YOLO, Object Recognition.

1. Introduction

Insulators play a vital role in the power system. They can separate the conductors from the structures, serving as an isolation to prevent the current from flowing through unexpected paths. They can also play a supporting role to bear the dynamic load of the conductors when they swing with the wind. Moreover, as an important measure for line insulation, they can ensure the reliability and stability of the power system.

However, the insulators of transmission lines work in the atmospheric environment and are subject to many destructive factors, such as natural aging, electrical aging, optical aging, and chemical aging, which may cause phenomena like flashover, aging, and even self-explosion of the insulators. If not dealt with in a timely manner, the tiny defects of the insulators caused by aging and other reasons will develop into permanent faults, which will cause great harm to the safety and economy of the power grid operation. In addition, the tiny defects that occur due to manufacturing processes and other reasons can also lead to permanent faults of the insulators. To reduce the harm caused by insulator damage, regular inspections are required. However, manual diagnosis is time-consuming and laborious and it is difficult to meet the requirements of large-scale and precise diagnosis of the power system. Therefore, we have improved the artificial intelligence algorithm to enhance the rapid diagnosis of insulators on a large scale and with high precision in various complex environments.

In recent years, some researchers have used deep learning algorithms to identify insulator defects. For example, Liao [1] introduced modules for low-resolution and small-target detection in the backbone network and achieved multi-scale feature fusion, which improved the detection ability of insulator self-explosion defects in the loaded environment. Wang [2] improved C2f based on YOLOv8 to enhance the model's positioning ability and achieved a more balanced detection of insulators with basically unchanged complexity. Yuan [3] introduced a high-performance multi-scale attention network with cross-space learning ability and proposed the C2fRFE module to improve the detection ability of insulators and their defects at different scales. Feng [4] improved the overall performance of the model by adopting a multi-stage transfer learning strategy. In addition, through information fusion, more accurate positioning of small targets of self-explosion defects was achieved to improve the detection of glass insulators and their self-explosion defects in complex environments. Lan [5] introduced a two-layer routing attention mechanism in the backbone network of the YOLOv8 model to increase the attention to global features, suppress the interference of unnecessary information, and improve the neck network, thereby achieving an improvement in detection performance. The research by Zhong [6] added a dynamic detection head for the problem of small defects of insulators, achieved the branch interaction between positioning and classification, and adjusted the prediction results. However, no improvement was made for the small classifications of pollution flashover and damage. The research by Wang [7] embedded the improved C3STR module at the end of the backbone network based on the YOLOv5s algorithm, which improved the detection ability of insulator string damage. Nevertheless, the improvement effect on the detection of pollution flashover and flashover was not significant.

However, small-target defects account for a relatively large proportion of insulator defects. At present, the targets of most insulator defect detection methods based on object detection networks are only limited to clear insulators, and there is still relatively little research on insulator defect detection in complex scenarios [8]. The above improvement methods have not been optimized for the identification of small-target insulator defects and their recognition effects are not good themselves. However, small-target defects play a non-negligible role in insulator damage. Therefore, this paper optimizes the problem of small-target insulator defect detection.

To address the above problems, this paper proposes the COK-YOLO algorithm based on the YOLOv8 algorithm. By drawing on the principle of Cross Stage Partial Network (CSPNet)[9], the COK-YOLO layer is proposed, and the Omni kernel is used to achieve feature extraction of global, large-scale, and local contents, which improves the detection ability of small insulator defects. Through experimental verification, compared with the situation before improvement, the mAP of the COK-YOLO algorithm proposed in this paper has increased by 2. Among them, the insulator category has increased by 4.1, the damaged category has increased by 5.7, and the flashover category has increased by 1.3. This proves the effectiveness of this experiment and meets the requirement of improving the detection ability of small insulator defects without increasing the computational difficulty.The basic funamental of BP neural network

2. The COK-YOLO Algorithm

2.1. The YOLOv8 Algorithm

The YOLOv8[10] is an object detection model developed by Ultralytics. Based on the previous successful versions of YOLO, it introduces new features and improvements, further enhancing its performance and flexibility. YOLOv8 is based on the design concepts of being fast, accurate, and easy to use, making it an excellent choice for a wide range of object detection, image segmentation, and image classification tasks. YOLOv8 algorithm mainly draws on the model advantages of algorithms such as YOLOv5, YOLOv6, and YOLOX, providing a brand-new target recognition model to meet the usage requirements in different scenarios. It mainly consists of three parts, including the backbone, neck, and head.

In the backbone part, drawing on the idea of the CSPDarkNet module, the CSP Bottleneck with 3 convolutions (C3) module in YOLOv5 is replaced with the Faster Implementation of CSP Bottleneck with 2 convolutions (C2f) module. The Spatial Pyramid Pooling (SPPF) module is retained, but with more skip connections and split operations, further achieving lightweight design.

For the neck part, it continues to use the idea of the Path Aggregation Network (PAN) structure. The fourth, sixth, and ninth layers are taken as the inputs of the PANet structure. After upsampling and channel fusion, the final results are obtained.

The head part adopts a decoupled head structure, separating the classification and detection heads into three detection heads to detect three different scales. The structure diagram of the neck part in YOLOv8 is shown in Figure 1. It accepts the outputs of three different levels produced by the backbone, and through feature processing and fusion, forms outputs of three different scales. The outputs of the three different scales are respectively used to detect targets of large, medium, and small levels. The small targets are responsible for extracting, synthesizing, and processing image features by the large-scale neck part. Therefore, in order to enhance the recognition ability of small-sized targets, this paper conducts enhancement processing on the large-scale feature maps of the neck.

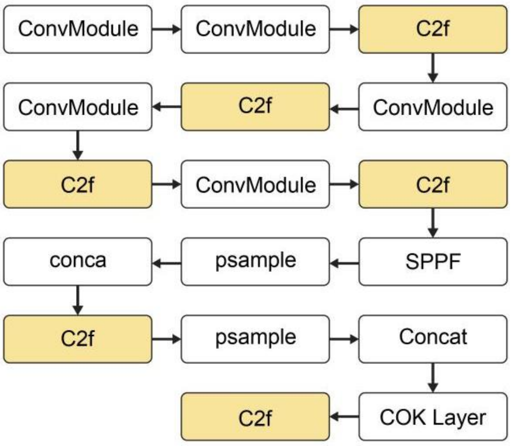

Figure 1. Structure diagram of the neck

2.2. COK Network

In terms of the specific improvement methods, this paper proposes the CSP-Omni Kernel Network (COK). By using the COK network, the processing of large-size feature maps in the neck is strengthened, enabling the overall network to better detect small target defects in images. In this paper, a COK layer is added after the Concat layer to enhance the learning ability of the YOLOv8 model, reducing the amount of computation while increasing the computing speed. The structure of the COK layer is shown in Figure 2.

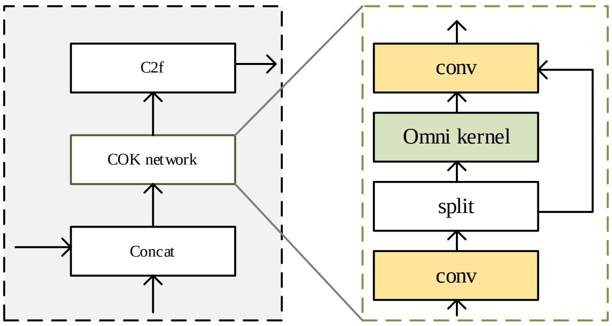

Figure 2. Structure Diagram of the COK Network

In the Figure 2, "conv" represents the convolutional layer,The size of the convolution kernel is 1×1, and the number of input channels is equal to that of output channels. The processing flow in this paper is as follows: the input convolution is split into two parts in the channel direction with a ratio of 1:3. Among them, the features of 1/4 channels are processed by the Omni Kernel network. After processing, they are spliced with the features of the remaining 3/4 channels and then a second convolution is performed to finally obtain the final output.

The COK network draws on the idea of the CSPNetwork, achieving lightweight while deepening the network depth to ensure accuracy. In addition, it can enhance the learning ability of the network, remove computational bottlenecks, reduce the use of video memory, and accelerate the inference speed of the network. These characteristics enable the COK network to quickly learn more feature information.

2.3. Omni Kernel Network

In this paper, the Onmi Kernel network is used in the COK network to strengthen the information processing of small target defects and improve the recognition effect of small-sized targets. In DCAM, the size of the convolution kernel is 1×1.The structure of the Onmi Kernel network is shown in Figure 3.

In the figure, DConv represents depthwise separable convolution, FFT represents Fourier transform, IFFT represents inverse Fourier transform, and GAP represents Global Average Pooling. The Omni kernel network is divided into three processing branches: local branch, large branch, and global branch. Among them, the local branch uses 1×1 depthwise convolution to process local small targets. The large branch uses 31×31 depthwise convolution to pursue a large receptive field. And a global branch is introduced to obtain rich context information. Finally, the results obtained from the three branches are summed up and then subjected to convolution processing. In this way, not only the enhanced processing of small target information is achieved, but also the acquisition of global information is ensured, ensuring that the overall recognition rate does not decrease.

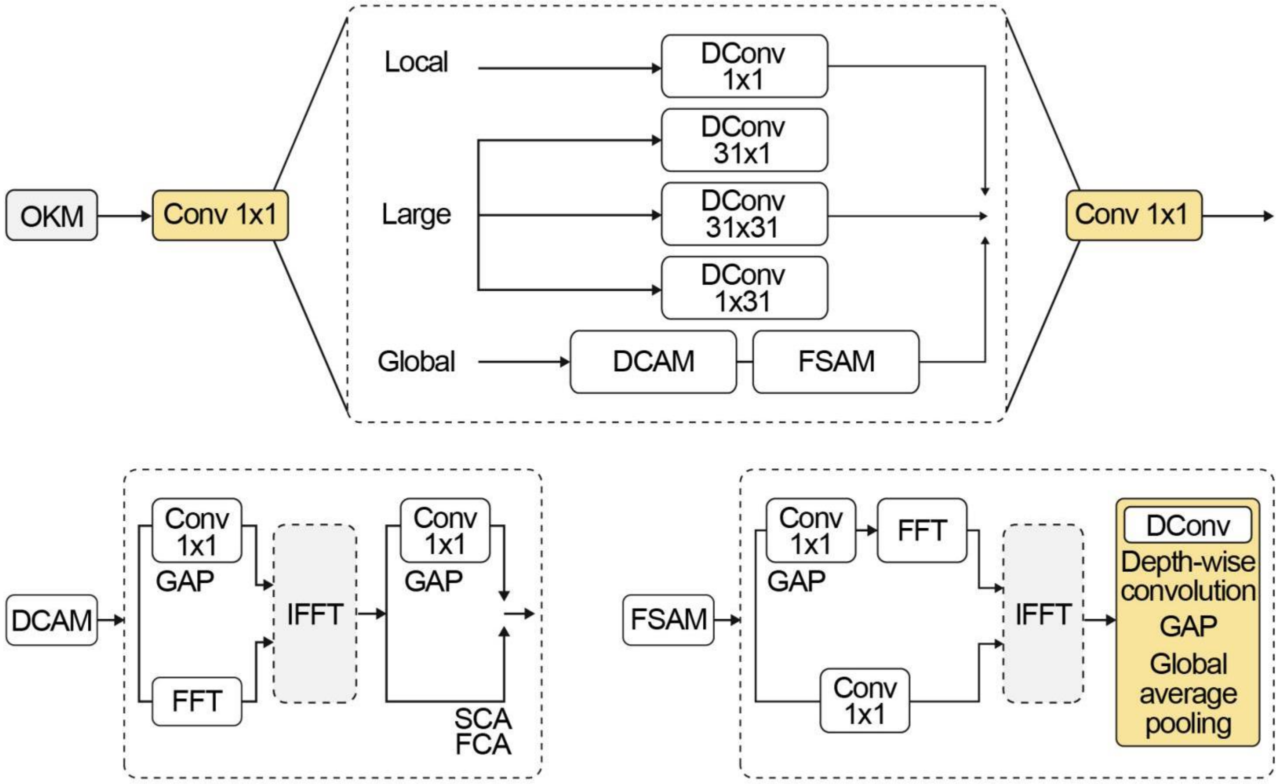

Figure 3. Omni Kernel Network

3. Experiment

To verify the actual effectiveness of the algorithm proposed in this paper, an algorithm detection and comparison experiment was designed. The theoretical structure in this paper was implemented using the PyTorch framework under the Python 3.8 environment. The operating system used was Ubuntu 20.40, the CPU was an AMD EPYC 9754 128-Core Processor, the GPU was an NVIDIA GeForce RTX 4090D, and the video memory was 24G.

3.1. Datasets and Experimental Parameters

The insulator defect dataset used in this experiment was obtained by combining publicly available datasets on the Internet and those taken by ourselves, with a total of 3700 pictures. Among them, there are 1300 pictures of normal insulators, 650 pictures of damaged insulators, and 1750 pictures of insulator flashover. In this experiment, the dataset was randomly divided into a training set, a test set, and a validation set at a ratio of 6:2:2. The specific training parameter settings in the implementation are as follows: the number of epochs is 800, the image size is 640×640, and the batch size is 64. The changes in the loss value and the mAP value during training are shown in Figure 4. It can be seen from the figure that the training has reached a convergent state. After training, the algorithm weights with good performance were obtained in this paper, and some recognition results are shown in Figure 4.

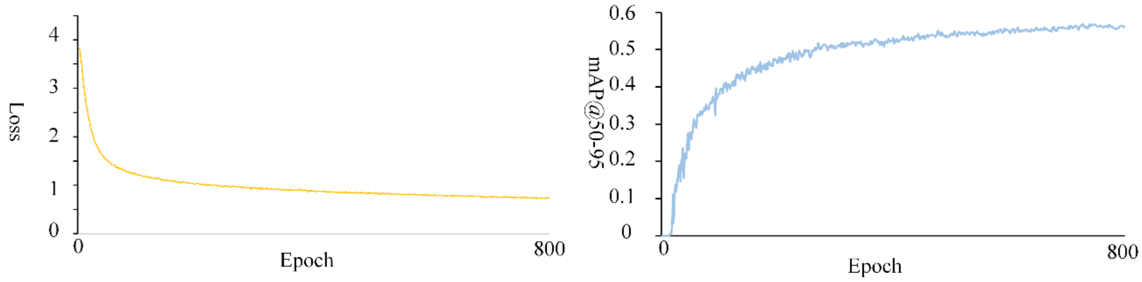

Figure 4. Training loss value and mAP

3.2. Comparative experiments and evaluation indicators

To verify the improvement effect, a comparative experiment was further conducted between the improved algorithm and the original YOLOv8 algorithm and YOLOv5 algorithm. This paper aims to solve the problem of accurately locating insulator defects. Therefore, mAP@50 and mAP@50/95, Average Precision (AP) of each category, and Giga Floating-point Operations Per Second (GFLOPs) were adopted as evaluation indicators in this experiment. mAP@50 and mAP@50/95 respectively represent the average value of AP of each category when the Intersection over Union (IoU) threshold is 0.5 and 0.5 - 0.95. AP represents the area on different recall rates, and the specific calculation formula of AP is shown in Equation (1) to (3). The larger the values of mAP and AP are, the more accurate the positioning is. And GFLOPs is a computational indicator for measuring the complexity of the mode.

Both the algorithms before and after the improvement were trained using the same parameters and datasets, and the optimal weights were taken as the training results. The experimental results after testing on the test set are shown in Table 1. It can be seen from Table 1 that the overall mAP of COK-YOLO has increased by 2 compared with the YOLOv8 algorithm and 4.4 compared with the YOLOv5 algorithm. Among them, the insulator category has increased by 4.7 and 4.8, the damaged category has increased by 5.1 and 9.5, and the flashover category has increased by 1.3 and 4. The recognition accuracy of each category has been effectively improved. Among them, the damaged and flashover categories belong to small targets, and their performance has been improved after the improvement, which can prove that the improvement method in this paper has a significant effect on improving the recognition of small target defects. In addition, the improvement range of the insulator category is also very significant, proving that the method in this paper can not only improve the detection effect of small targets, but also has a certain improvement effect on large targets.

In addition, the complexity of the improved algorithm has not increased significantly. Before the improvement, the GFLOPs was 3,006,233. After the improvement, it became 3,332,921, with an increase of 10.87%. The size of the algorithm has not increased significantly. While the complexity has not increased significantly, the accuracy of the experimental detection has been improved remarkably. To further test the real-time performance of the COK-YOLO algorithm proposed in this paper, an experiment on real-time detection was carried out. In this paper, 200 images were preheated first by using the weights in the previous algorithm, and then detection was conducted among 1,000 images. After obtaining the total time, the Frames Per Second (FPS) of the algorithm in this paper was calculated to be 251.3. It has been proved that the algorithm in this paper has a certain real-time performance while ensuring relatively high accuracy. Through the above experiments, the effectiveness of the method proposed in this paper has been proved.

$$P = \frac{TP}{TP+FP} \times 100\% \tag{1}$$

$$R = \frac{TP}{TP+FN} \times 100\% \tag{2}$$

$$\mathrm{AP} = \int_{1}^{0} \mathrm{P(R)dR} \tag{3}$$

Figure 5 shows the detection results of insulator defects after improvement. It can be seen from the figure that the defect detection of insulators has been significantly improved and the detection accuracy is relatively high. This also illustrates that the method introduced in this paper can enhance the detection ability of small defects of insulators.

Figure 5. Insulator Defect Recognition Results

Table 1. Results of the Comparative Experiment

Algorithm	GFLOPs	mAP@50(%)	mAP@50-95(%)	AP(%)		
				Insulator	Damaged	Flashover
YOLOv5	2503529	83.6	55.6	94.3	79.9	71.6
YOLOv8	3006233	86	56.9	94.4	84.3	74.3
COK-YOLO	3332921	88	58.5	99.1	89.4	75.6

4. Conclusions

Aiming at the problem that it is difficult to detect small-target defects of insulators, this paper proposes COK-YOLO. The COK layer is introduced into the neck part of the YOLOv8 algorithm. Drawing on the CSP theory, this layer enables the detection of more features. The Omni kernel is used to reasonably expand the convolution kernel to the feature size without a large number of parameters, thus completing the extraction of global, large-scale, and local contents. Through the above innovations, the recognition accuracy of the network for small-target defects is improved.

Verified by experiments, the mAP has been improved by 2.0 compared with that before the improvement. Specifically, the mAP of the insulator category has increased by 4.1, that of the damaged category has increased by 5.7, and that of the flashover category has increased by 1.3. This proves the effectiveness of the COK-YOLO method proposed in this paper, achieving the effect of enhancing the ability to detect small insulator defects without increasing the computational complexity.

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