DFW-YOLO: A small insulator target defect detection algorithm based on improved YOLOv8s

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Abstract

With the continuous progress of deep learning technology, UAV aerial photography faces significant challenges for insulator defect detection. Aiming at the problems of low detection accuracy of existing target detection algorithms and difficulty in recognizing small target defects, we propose an improved small target insulator defect detection algorithm based on YOLOv8s, named DFW-YOLO. Firstly, the Detect_Efficient lightweight detection header is proposed using partial convolution (PConv) to lighten the original detection header. Secondly, a FocalModulation focal modulation module is introduced into the backbone network to enhance the model's extraction and fusion capabilities for features at different scales. Finally, to enhance the model's focus on poor-quality samples and reduce the harmful gradients they produce, a loss function with a Wise-IoU V3 dynamic non-monotonic focusing mechanism is used instead of the original CIOU loss function. We conducted experiments on a publicly available dataset of UAV aerial photography. According to the experimental data, DFW-YOLO achieves an 86.8 % mAP in insulator defect detection, showing a 6.8 % improvement compared to the original YOLOv8s model and generally exceeding the performance of other prominent models. Utilizing this method can effectively boost the accuracy of identifying insulator defects in small targets.

Keywords: Deep learning, YOLOv8, insulator defect detection, focus modulation, pconv, Wise-IoU V3.

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Introduction

Insulators, as key components in power systems, have the important function of preventing current from returning to the ground and supporting conductors [1]. Studies have shown that about 82 % of electrical faults in transmission lines are caused by insulator defects [2]. As insulators are exposed outdoors for a long time, they are easily affected by dust, dirt, and bad weather, and their defects are complex, which makes them prone to failures during power transmission. Especially in high-voltage transmission lines, any transmission and distribution faults may bring huge economic losses to enterprises or departments. Therefore, detecting insulator defects (e.g., tainted flash, breakage, detachment, etc.) [3] is an important task in transmission lines. In recent years, with the development of drone technology [4, 5, 6], drones have gradually replaced the traditional manual inspection [3], which greatly facilitates insulator defect detection. This not only saves manpower and material resources but more importantly, reduces the dangers that inspectors may encounter in the inspection process.

Conventional insulator defect detection is mainly performed by observation methods [7], ultrasonic detection [8] or conventional image processing methods [9]. Although some progress has been made in insulator defect recognition, these methods appear to be time-consuming and labour-intensive in the case of complex transmission line structures and backgrounds. In addition, the large size and number of images captured by UAVs pose challenges for the identification of complex backgrounds and small defects. Therefore, there is an urgent need for a method that can detect small target insulator defects in complex backgrounds to meet the demand for real-time fault investigation in power systems. Considering the evolution of deep learning and the limitations associated with traditional algorithms [10] , neural network-based target detection algorithms have emerged. Compared with traditional algorithms, neural network algorithms have significant advantages in detection accuracy and speed and reduce the impact of complex environments on the detection effect. Zheng et al. [11] used convolution neural networks to extract features from aerial images and successfully detected insulator self-explosion defects, which improves the robustness and practicality of detection. However, the training process of R-CNN is more complicated and impractical to apply in complex backgrounds. Ji et al. [12] used ResNet50+FPN to replace the feature extraction network of Faster R-CNN, optimised the anchor point scale of the RPN network, and improved the original loss function using Focal Loss, which improved the detection accuracy of insulators but could not meet the real-time detection. The YOLO algorithm has rapidly become a hotspot in the field of target detection due to its end-to-end design and powerful scalability. Therefore, more and more researchers apply it to the insulator detection field. Hao et al. [13] redesigned the backbone network using cross-stage partial and residual partitioned attention networks and added a bidirectional feature pyramid network to improve the detection of defects of small-target insulators in complex backgrounds. Based on YOLOv8, Liu et al. [14] constructed a weather-domain integrated network to simulate a variety of realistic weather scenarios and developed a cross-modal information module (CIA-YOLO) using the attention mechanism to enhance insulator defect detection. Although these methods improve the detection accuracy to a certain extent, they are still deficient in multi-scale feature extraction and fusion of insulator defects, resulting in poor detection performance of the model in complex backgrounds.

In response to the above analysis, this paper aims to propose an algorithm for small target insulator defect detection based on YOLOv8s improvement. To further solve the problem of small target insulator defects in complex backgrounds. Specifically, the main contributions of this work are as follows:

1. Based on the YOLOv8s detection head, a lightweight detection head (Detect_Efficient) is proposed in combination with partial convolution (PConv), which reduces excessive feature redundancy in the feature extraction process and further improves the detection speed of the model.
2. Introducing a focus modulation module in the backbone network enhances the model’s ability to focus on specific targets. It also improves feature extraction and fusion under complex backgrounds.
3. Using the loss function of the Wise-IoU V3 version instead of CIOU, the model better weighs different samples, further focuses on low-quality samples, and improves computational efficiency.

1. Related work

This section reviews the relevant literature on insulator defect detection. Early insulator defect detection mainly relied on manual inspection [15], especially in extreme weather conditions, this work becomes particularly difficult to meet the requirements of real-time detection. With the development of the social economy, the demand for electricity in various industries is increasing, and insulator defect detection has gradually developed. Since 2012, deep learning [16, 17, 18]related algorithms have become popular, and researchers have begun to apply them to the field of insulator defect detection and play an important role. Deep learning-based insulator defect detection target detection [19] algorithms are mainly divided into two categories:

One class is two-stage target detection algorithms, including R-CNN [20], SPPNet [21], Fast R-CNN [22], Faster R-CNN [23], Mask R-CNN [24], etc. Zhao et al. [25] improved Faster R-CNN by using a feature pyramid network and used hue, saturation and HSV colour space adaptive thresholding to Segmentation of the image enabling better recognition of normal insulators and their faulty insulators. The average accuracy of this method is 90.8 % for glass insulators and 91.7 % for composite insulators. Ling et al. [26] combine Faster R-CNN with U-Net, the former improves the signal-to-noise ratio, and the latter accurately classifies pixels in cropped images of different sizes, and the accuracy of insulator detection reaches 94.9 %. Zhou et al. [27] improve the structure of ResNet101 in the backbone part of Mask R-CNN. Part to improve the structure of ResNet101 by adding the attention mechanism, so that the model is more sensitive to small targets and can quickly identify the location of small targets. And improve the loss function and integrate the rotation mechanism into the loss function formula, so that the average accuracy of insulators is as high as 98 %.

The other category is single-stage target detection algorithms, including YOLO, SSD [28], RetinaNet [29], etc. Luan et al. [30] enhanced the model feature abstraction process and improved the accuracy of insulator fault detection by adding a downsampling module to the YOLOv5 backbone as well as using a spatial pyramid to extend the convolution module in the neck. He et al. [31] used YOLOv8n as the benchmark model and constructed a multi-scale fusion structure ResPANet to replace PANet, which improved the average accuracy of the model from 89.2 % to 93.9 %. Zhang et al. [32] added a global attention mechanism to YOLOv5s in their study and improved on C3 by emphasising on the retention of key information, feature extraction and fusion. Finally, SPPF is improved to IL-SPPFCSPC, which enhances the model’s attention to key information and global information and improves the multi-scale fusion capability. Compared with YOLOv5, this improved model improved insulator detection accuracy by 3.6 % and enhanced the model’s ability to recognise insulator defects in complex backgrounds. Ding et al. [33] studied the introduction of the Ghost convolution module and integrated an attention mechanism based on coordinate attention (CA) to improve the YOLOv5s, and the introduction of the EVCBlock to enhance the neck network to obtain a better feature representation, resulting in an accuracy of 94.2 % for insulator defects.

For the existing target detection models, although the two-stage detection model shows excellent performance in terms of accuracy, its large number of parameters brings a complex computational burden, which is difficult to achieve by resource-limited devices; while the single-stage detection model, although suitable for deployment, has low insulator detection accuracy in the complex context of power systems. Therefore, this paper proposes a target detection algorithm DFW-YOLO based on YOLOv8s to meet the requirements of small target insulator defect detection in complex backgrounds.

2. Proposed method

The structural design of the DFW-YOLO network proposed in this paper is shown in Fig. 1. Firstly, to achieve the identification of insulators under complex background, this paper introduces the Focalmodulation focal modulation module to replace the SPPF module, which is more sensitive to the feature information of insulators under different scales, and has a higher accuracy of identifying defects of insulators; secondly, to achieve the model's lightness, this paper uses the PConv to improve the original detector head of YOLOv8, defined as Detect_efficient, it makes the model better to deal with the problem of insulators being occluded; finally, the boundary box regression loss function of the Wise-IoU V3 dynamic focusing mechanism is introduced, which reduces the detrimental gradient generated by low-quality samples, and in this way, it motivates the improved model to be more focussed on the samples of common quality and improves its overall performance.

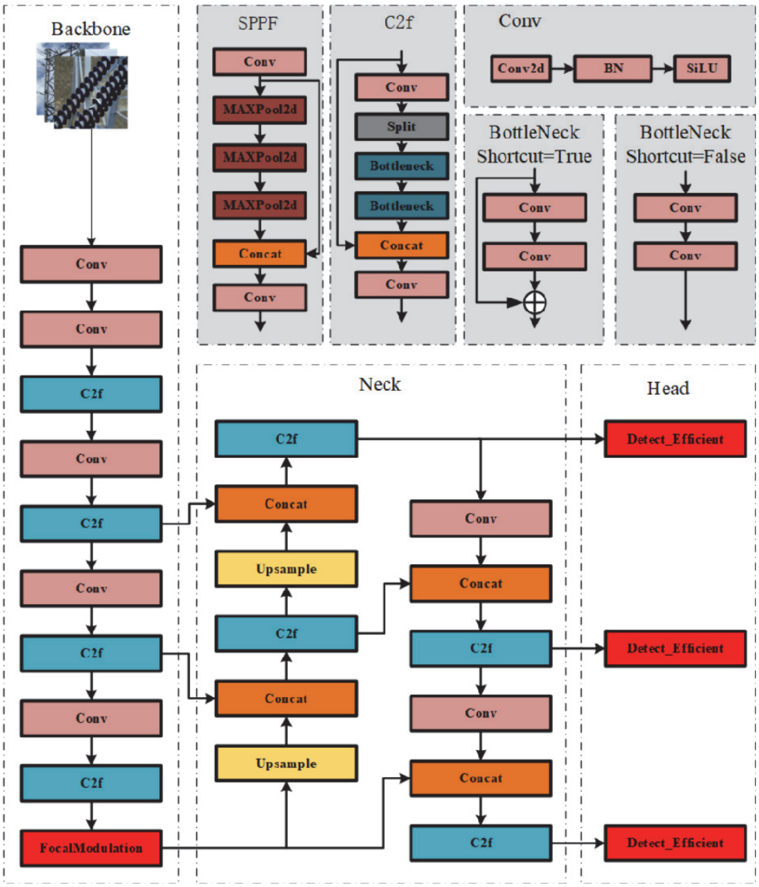


Fig 1. The structure of Proposed Model

2.1. Detect_Efficient (DetectE)

The partial convolution (PConv)[34] mentioned in this paper was proposed by Chen et al. During their research, they found that the feature maps in different channels are highly similar, which leads to redundancy of the feature maps, and thus proposed the concept of partial convolution. The structure is shown in Fig. 2, and the memory access for partial convolution is only a quarter of that for normal convolution (e.g., Fig. 3) which is able to reduce the amount of computation while increasing the FLOPS, thus improving the model training speed. Compared with the original detection head that uses full convolution for feature extraction, we introduce Partial Conv3 to perform convolution operation on some channels, which retains the original features while enhancing the feature extraction capability. As shown in Fig. 4, This module is embedded into the YOLOv8 detector head, which reduces the number of parameters compared to the original version, and keeps the same number of channels in the input and output, which is suitable for resource-constrained devices.

2.2. Focal Modulation (FM)

The focus modulation module was proposed by Yang et al. [35]. As shown in Fig. 5, It can encode the context space at different scales and adaptively aggregate based on the query, thus helping the model to focus more on specific regions of the object. This technique, centred on focus modulation, contains a multi-layer feature fusion mechanism and improves the model performance according to the size of the detected object. It better captures defective insulators in complex backgrounds, making YOLOv8s more sensitive to defective insulator regions. Therefore, Focal Modulation is used to replace the SPPF module in YOLOv8.

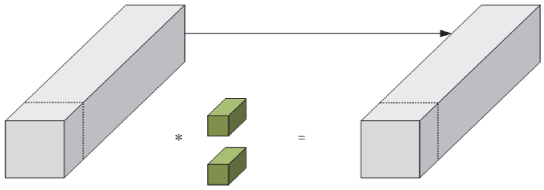


Fig. 2. The structure of Partial Convolution

2.3. Wise-IoU V3 LossFunction

Tong et al.[36] proposed a Wise-IoU method based on a non-monotonic focusing mechanism. First, they constructed the bounding box loss function of wise-IoU V1 based on distance attention, which can be derived from Eq. 1 to Eq. 3. Second, they improved wise-IoU V2 based on focal loss and designed a monotonic focusing mechanism, effectively reducing the negative impact of low-quality samples on detection accuracy. For the harmful gradients generated by low-quality samples, they assigned gradient gains to focus the bounding box regression on low-quality anchor frames. Ultimately, a nonmonotonic focusing coefficient β was developed based on Wise-IoU V1, culminating in the creation of Wise-IoU V3 with a dynamic nonmonotonic focusing mechanism.

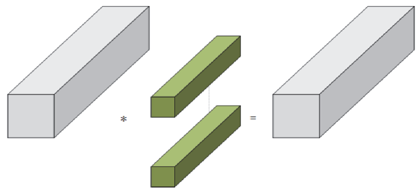


Fig. 3. The structure of Convolution

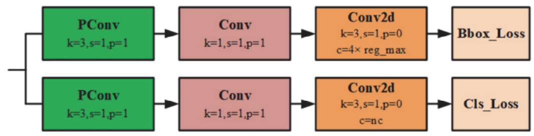
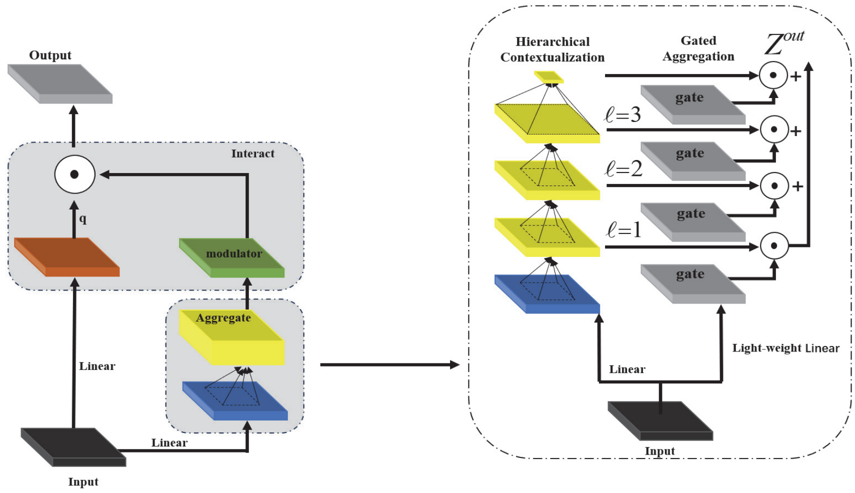


Fig. 4. The structure of Detect_Efficient



a) FocalModulation b) Context Aggregation

Fig. 5. a) Focalmodulation, b) for detailed structure of context aggregation

In this study, DFW-YOLO replaces the CIOU used in the original YOLOv8 with Wise-IoU V3 for calculating the bounding box regression loss, which can be derived from Eq. 4 to Eq. 5. Firstly, it has a dynamic non-monotonic mechanism; secondly, Wise-IoU uses outliers instead of IOU to evaluate the quality of the anchor frame; and finally it can better weigh high and low-quality samples. Its expression is as follows:

$$\mathcal{L}_{IoU} = 1 - IoU \,, \tag{1}$$

$$\mathcal{L}_{WIoUv1} = \mathcal{R}_{WIoU} \mathcal{L}_{IoU} \,, \tag{2}$$

$$\mathcal{R}_{WIoU} = \exp\left(\frac{\left(x - x_{gt}\right)^2 + \left(y - y_{gt}\right)^2}{\left(W_g^2 + H_g^2\right)^*}\right), \tag{3}$$

$$\beta = \frac{\mathcal{L}_{IoU}^*}{\mathcal{L}_{IoU}} \,, \tag{4}$$

$$\mathcal{L}_{WIoUv3} = r \mathcal{L}_{WIoUv1}, r = \frac{\beta}{\delta \alpha^{\beta - \alpha}} \,, \tag{5}$$

where $\mathcal{L}_{IoU}$ belongs to the bounding box loss, $\mathcal{R}_{WIoU}$ belongs to the distance attention. x, y are the coordinates of the anchor frame. x_{gt}, y_{gt} are the coordinates of the target frame. W_g, H_g are the height and width of the real frame. In this paper, regarding the hyperparameters $\alpha = 1.7$, $\beta = 2.7$.

3. Experiments

3.1. Datasets

The first dataset is from Roboflow's publicly available dataset, Detector de Fallas en Aisladores Dataset (DFAD), which contains 1607 photos covering Glassdirty, Glassloss, Polymer, Polymerdirty, Two glass, Broken disc, Insulator, Pollution-flashover, Snow nine categories. Fig. 6 shows images of each category of insulators.

The second dataset is SFID, a brand new dataset constructed by Zhang et al.[37] by data enhancement of the UPID dataset through synthetic fogging algorithm, which contains 13718 training and test images. The dataset contains two categories: normal insulators and insulators with defects. The labelling information is shown in Tab. 1.

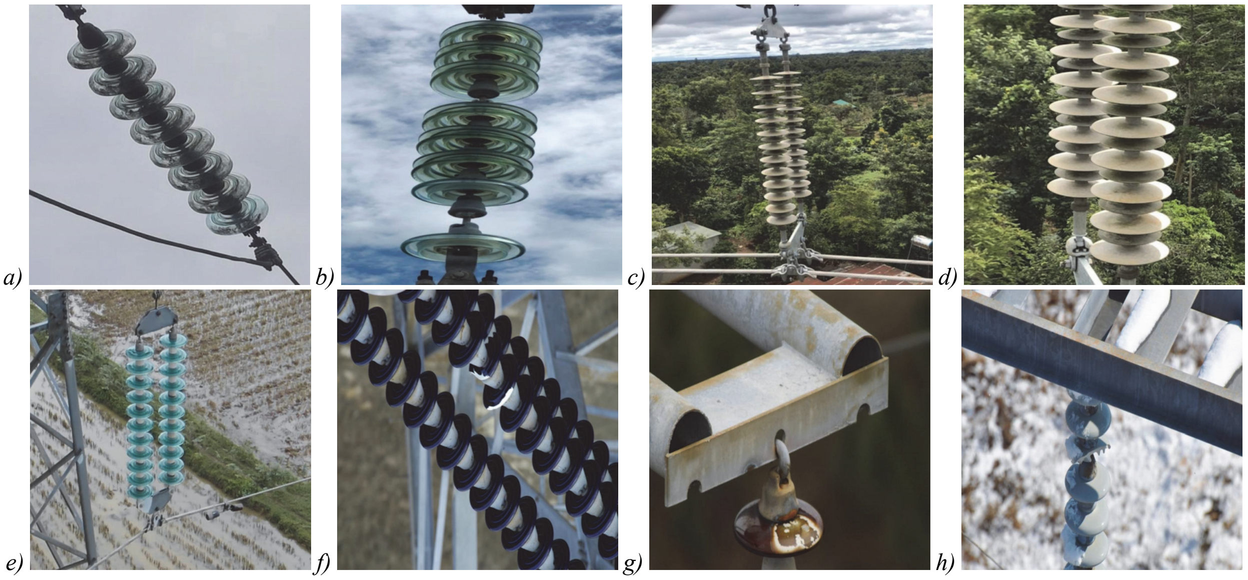


Fig. 6. Images for each category of insulator: a) Glassdirty, b) Glassloss, c) Polymer, d) Polymerdirty, e) Two glass, f) Broken disc, g) Pollution-flashover, h) Snow

Tab. 1. Information on the number of labels for SFID

Dataset	Labels name	Number of labels
SFID	insulator	21188
	broken_piece	3958

3.2. Experimental Setup

The remote server used in this paper runs on Linux with a 12-core Intel(R) Xeon(R) Platinum 8255C CPU @ 2.50GHz, RTX 2080 Ti GPU, and 11GB of video memory. The software configuration consists of PyTorch 1.9.0, Python 3.8 (Ubuntu 18.04), and Cuda 11.1. Both of the above datasets are divided into training, validation, and test sets in the ratio of 8:1:1. We used the SGD optimiser for hyper-parameter fine-tuning, with batch size set to 16 and epochs set to 200.

3.3. Evaluation metrics

In this experiment, the evaluation metrics used to evaluate the performance of the insulator defect recognition algorithm are Parameters, average precision mAP, precision P, and recall R to evaluate the performance of the model as a whole. In Eq. 6, K_h denotes the height of the convolutional kernel, K_w denotes the width of the convolutional kernel, C_{in} denotes the number of input channels and C_{out} is the number of output channels. In Eq. 7 and Eq. 8, AP is the recognition accuracy of a single insulator category, and N is the number of categories of all insulators in the dataset. mAP is the average of the recognition accuracies of all insulators. In Eq. 9 and Eq. 10, TP is the number of objects that the model correctly identifies as insulators that are insulators, TN is the number of objects that the model correctly identifies as non-insulators that are not insulators, FP is the number of misidentified as insulators, the number of objects that the model incorrectly identifies as insulators that are not insulators, and FN is the number of objects that the model incorrectly identifies as non-insulators that are insulators.

$$Paras = (K_h \times K_w \times C) \times C_{out} + C_{out} , \tag{6}$$

$$AP = \int_0^1 P(R) d(R) , \tag{7}$$

$$mAP = \frac{\sum_{i=1}^{N} AP_i}{N} \times 100\% , \tag{8}$$

$$P = \frac{TP}{TP + FP} \times 100\% , \tag{9}$$

$$R = \frac{TP}{TP + FN} \times 100\% . \tag{10}$$

3.4. Analysis of experimental results

3.4.1. Performance comparison with current mainstream target detection algorithms

To validate the performance of our proposed algorithm DFW-YOLO model, we compare it with YOLOv5s, YOLOv7-tiny, YOLOv8s, and YOLOv10s trained on the DFAD dataset and analyse it. The reason for comparison with these models is that they are all representative of the target detection domain.

As can be seen from the Tab. 2, the DFW-YOLO model proposed in this paper has significant advantages over the current mainstream YOLO series of detection models. In detail, the Params, P, R and mAP of the classical lightweight YOLOv7-tiny version are 6.036×10^6, 59.4 %, 55.2 % and 20.2 %, respectively. The YOLOv7-Tiny model is not suitable for insulator defect detection tasks in complex backgrounds due to its minimal number of parameters and relatively lightweight, which adversely affects insulator detection with low detection accuracy. The mAP50 accuracy of YOLOv5s is higher than that of YOLOv8s and YOLOv10s, but the mAP50-95 accuracy of YOLOv8s is much higher than them, which helps to identify insulators in complex backgrounds. This explains why we chose YOLOv8s as the benchmark model. The mAP50 and recall of the DFW-YOLO model proposed in this paper are 86.8 % and 84.3 %, respectively. Its number of parameters only increases by 7.64 % based on YOLOv8s, which is moderate in computation, and the detection performance is improved to meet the requirements of UAVs for insulator defect detection. In addition, the accuracy of DFW-YOLO reaches 84.6 %, which is at the state-of-the-art level. Overall, our proposed DFW-YOLO achieves accurate detection in insulator defect target detection with optimal results and is suitable for insulator defect detection tasks.

Tab. 2. Performance comparison of different models on DFAD dataset

Dataset	Models	Params(M)	GFLOPs	P	R	mAP50	mAP50-95
DFAD	YOLOv7-Tiny	6.036M	13.2	0.594	0.552	0.504	0.202
	YOLOv5s	7.034M	15.8	0.803	0.831	0.825	0.416
	YOLOv10s	8.042M	24.5	0.668	0.734	0.741	0.435
	YOLOv8s	9.309M	27.0	0.811	0.749	0.800	0.460
	DFW-YOLO	10.02M	21.8	0.846	0.843	0.868	0.468

3.4.2. confusion_matrix_normalized

In addition to the evaluation metrics mentioned in the previous section, we also use the confusion matrix to measure the model's accuracy. The YOLOv8s confusion matrix is shown in Fig. 7, and the DFW-YOLO confusion matrix is shown in Fig. 8. The vertical axis represents the predicted results of the model and the horizontal axis represents the actual results. In comparison, the recognition accuracy of DFW-YOLO in the categories of Glassdirty, Glassloss, Polymerdirty, Broken disc, and Pollution-flashover are all improved, and the misrecognition rates of some categories are reduced. This shows that our improvements are effective. However, there is still room for further optimization to recognise the Polymerdirty category.

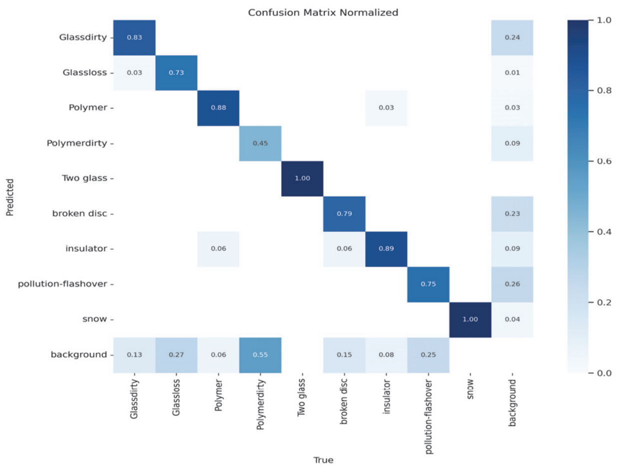


Fig. 7. YOLOv8s confusion matrix

3.4.3. Comparative experiments on SFID

In order to verify the generalisation performance of DFW-YOLO, we conduct experiments on publicly available insulator defect datasets. The experimental results are shown in Tab. 3. DFW-YOLO not only achieves good results on the accuracy side, but also keeps the computational volume moderate.

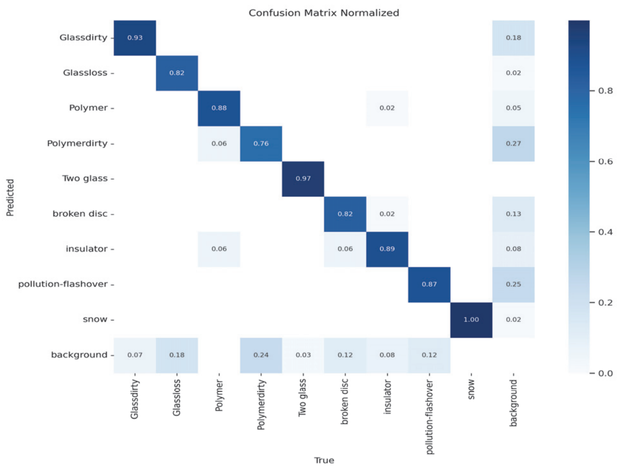


Fig. 8. DFW-YOLO confusion matrix

Tab. 3. Experimental results on SFID

Dataset	Models	mAP0.5(%)	mAP0.5:0.95(%)
SFID	Faster RCNN	98.0	78.8
	Mask RCNN	97.8	79.6
	YOLOv5	98.8	83.1
	YOLOv6	98.9	83.5
	YOLOv7	99.0	82.0
	YOLOv8	99.0	82.4
	DFW-YOLO	99.3	84.8

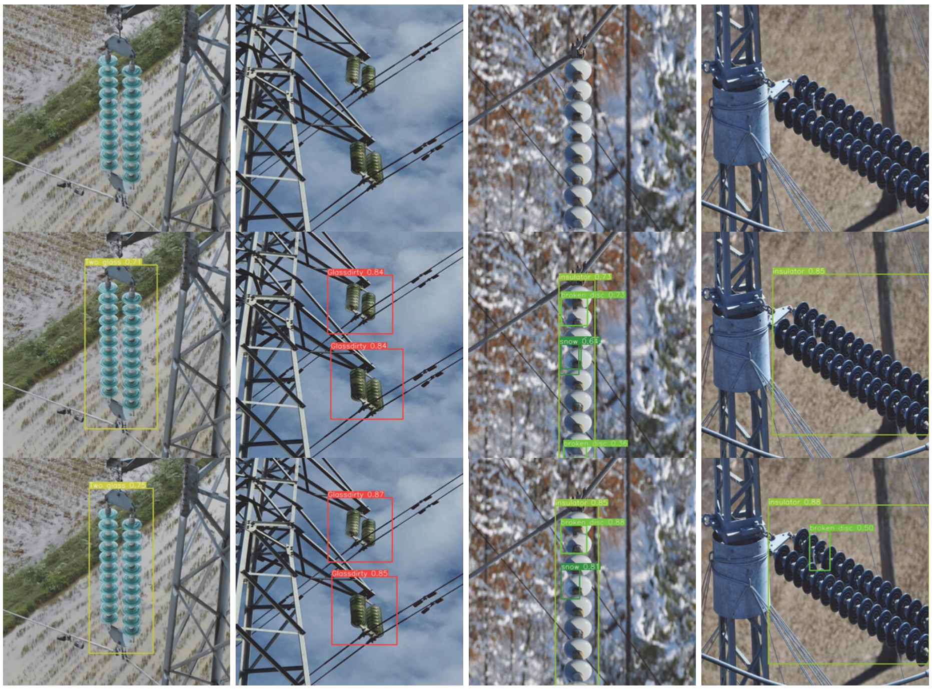
3.4.4. Ablation Experiment

To verify the effectiveness of each of our proposed improvement strategies, we conducted ablation experiments on YOLOv8s. The results are shown in Tab. 4, where each improvement strategy applied to the benchmark model improves the detection performance to different degrees. Model A, which replaces the original SPPF module of YOLOv8 with the Focal focus modulation module, improves the recall by 4.5 % and the mAP50 to 81.1 %. This indicates that the Focal Modulation Module improves the feature fusion and feature extraction capabilities of the model, making the model more sensitive to specific regions. Model B improves the original detection head of YOLOv8 using partial convolution (PConv), and the mAP50 is improved by 1.9 %, which decreases the computational complexity of the model while enhancing the detection of insulator defects. Model C uses the Wise-IoU V3 version of the loss function to replace the original CIOU of YOLOv8, which reduces the regression difficulty of the loss function, enhances the model's focus on low-quality samples, and improves the mAP50 by 3 %. Models D, E, and F are combinations of any two of Focal, DetectE, and Wise-IoU V3, respectively, and experiments show that each combination improves detection accuracy. Model G is the DFW-YOLO model proposed in this paper, which improves the mAP50 by 6.8 % compared with the original YOLOv8s.

The detection results are shown in Fig. 9. The sequence of images in the figure, from top to bottom, includes the original, YOLOv8s detection, and the detection by the proposed DFW-YOLO. In Fig. 9*a*, insulator detection is relatively easy when the paddy field is the background, and the detection accuracy of our proposed model is 4 % higher than that of YOLOv8s. In Fig. 9*b*, insulator defect recognition becomes difficult in the background of complex structured towers. However, DFW-YOLO continues to exhibit higher recognition accuracy compared to YOLOv8s. In Fig. 9*c*, in the complex background of snowy days, trees and power lines, DFW-YOLO can accurately recognise the corresponding defects with a precision better than that of YOLOv8s, whereas misdetections occurred in YOLOv8s. In Fig. 9*d*, when the normal insulator string is extremely similar to the broken insulator string, DFW-YOLO still detects it correctly, while YOLOv8s suffers from missed detection.

Tab. 4. Ablation experiments in the module of the proposed methodology

Models	Focal	Detect E	wiou v3	Parms(M)	GFLOPs	P	R	mAP50	mAP50-95
YOLOv8s				9.309	27.0	0.811	0.749	0.800	0.460
A	✓			11.542	28.8	0.780	0.794	0.811	0.435
B		✓		9.614	21.5	0.719	0.837	0.819	0.428
C			✓	9.309	27.0	0.831	0.809	0.830	0.455
D	✓	✓		10.028	21.8	0.836	0.808	0.847	0.447
E	✓		✓	11.525	28.8	0.809	0.850	0.864	0.456
F		✓	✓	9.614	21.5	0.841	0.852	0.864	0.466
G	✓	✓	✓	10.028	21.8	0.846	0.843	0.868	0.468



a) b) c) d)

Fig. 9. Comparison of actual test results on DFAD dataset: a) Paddy field background, b) Pole tower background, c) Complex background in snowy weather, d) Dense and similar insulator strings

Conclusion

In this paper, we propose a small target insulator defect detection algorithm DFW-YOLO based on improved YOLOv8s. The algorithm captures the feature information of insulator defects at different scales to be more sensitive to the features of their small-target defects. It enhances the backbone and head of YOLOv8s to solve the problem of difficult identification of small-target insulator defects in a complex background. Firstly, partial convolution (PConv) is combined with the detection head of YOLOv8 to reduce redundancy in the feature extraction process. Secondly, we introduce the FocalModulation module into the backbone network to enhance the model's extraction and fusion of insulator defect features at different scales. Lastly, the original CIOU is replaced by the Wise-IoU V3 loss function to improve the model's ability to extract features from low-quality samples and reduce the computational effort. Based on these improvements, comparison and ablation experiments with existing algorithms are conducted on public insulator datasets. The experimental results show that DFW-YOLO effectively solves the problem of insulator defects occupying a small area in UAV aerial pictures and being difficult to identify in complex backgrounds. Future work will be devoted to achieving model lightweight while maintaining model recognition accuracy, and further applying the proposed model to real insulator defect detection scenarios to gain real-time and effectiveness.

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