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Research Article

A Transmission Line Defect Detection Method Based on YOLOv7 and Multi-UAV Collaboration Platform

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In order to prevent the economic losses caused by large-scale power outages and the life safety losses caused by circuit failures, the main purpose of this paper is to improve the efficiency, accuracy, and reliability of transmission line defect detection, and the main innovation is to propose a transmission line defect detection method based on YOLOv7 and the multi-UAV collaboration platform. First, a novel multi-UAV collaboration platform is proposed, which improved the search range and detection efficiency for defect detection. Second, YOLOv7 is used as a detector for multi-UAV collaboration platform, and several improvements improved the efficiency of defect detection under complex backgrounds. Finally, a complete transmission line defect images dataset is constructed, and the introduction of several defect images such as insulator self-blast and cracked insulators avoids the problem of low application value of single defect detection. The results indicate that the proposed method not only enhances the detection range and efficiency but also improves the detection accuracy. Compared with YOLOv5-S, which has good detection performance, YOLOv7 improves accuracy by 1.2%, recall by 4.3%, and mAP by 4.1%, and YOLOv7-Tiny achieves the fastest speed 1.2 ms and the smallest size 11.7 Mb. Even if the images contain complex backgrounds and noises, a mAP of 0.886 can still be obtained. Therefore, the proposed method provides effective support for transmission line defect detection and has broad application scenarios and development prospects.

1. Introduction

To ensure the safe operation of transmission lines, power departments must regularly inspect transmission lines and power systems [1]. Insulators are the key components in transmission lines, and they are mainly used for electrical insulation and mechanical fixation of power systems [2]. Affected by mechanical structure damage, material aging, and natural factors, the insulators often suffer from self-blast, damage, pollution, chip shedding, and other failures [3]. Wire, iron wire, vine, thatch, cloth, and excrement are commonly used materials for birds to build nests, leading to insulator flashover and short-circuit fault. In extreme weather, insulator defects often lead to instability of transmission lines and even lead to power outages and safety accidents. Therefore, the detection and identification of transmission line defects is important.

The traditional manual inspection methods are low inefficient and high risky and have low accuracy [4]. In recent years, unmanned aerial vehicle (UAV) technology has been applied to the inspection tasks of high-voltage transmission lines and power equipment [5]. By equipping various sensors and carrying appropriate object detection models, the transmission line monitoring equipment can complete the inspection tasks such as image acquisition, defect detection, and defect location for transmission lines

[6]. However, the UAV system is limited by the impact of flight costs, endurance, and complex environments, and the detection results rely on human subjective experiences. Since the video and image data of transmission lines can be effectively collected, UAV image acquisition, image processing [7], image fusion [8], and object detection have gradually become commonly used transmission line defect detection methods. Therefore, the main research content of this paper is to propose an efficient multi-UAV coordination system to reduce flight cost and improve data collection efficiency. In addition, an accurate and reliable defect detection model is also the main research content of this paper.

The transmission line defects detection methods based on the object detection algorithm can identify the transmission line defects, which is convenient for power workers to detect power failures early and reduce the occurrence of power accidents. Han improved the semantic feature extraction capability of the U-Net segmentation by embedding efficient channel attention (ECA-Net) module [9]. Zhang reconstructed the convolutional layer of the inception network through interleaved group convolution [10], which improves the generalization of insulator defect detection. Although the abovementioned methods can identify the types of insulator fault, the location of insulator defects cannot be accurately located. Many scholars use two-stage detection methods such as the region-based convolutional neural network (R-CNN), Faster R-CNN [11], and CenterNet [12] to detect and locate defects and faults in transmission lines. Lei and Sui proposed an insulator and bird's nest identification method based on the Faster R-CNN with the regional proposal network [13]. Liu et al. used the Faster R-CNN as the detector to achieve the slippage fault diagnosis of dampers in aerial images [14]. Xia et al. introduced a spatial and channel attention mechanism convolutional block attention module (CBAM) into CenterNet to improve the prediction accuracy of insulator and replaced the ResNet-50 by the lightweight MobileNet to speed up detection speed [15]. In addition, single shot detector (SSD) and you only look once (YOLO) are the most commonly used transmission line defect detection algorithms. Compared with the two-stage method proposed above, the methods do not have the step of extracting candidate regions through a regional proposal network (RPN), so it is fast and less accurate, and the YOLO series is a typical representative of them. Xin et al. proposed a small object detection algorithm named FA-SSD to solve the problem of the umbrella disc shedding occupying only a small proportion of an aerial image, in which deep features and shallow features are combined, and attention mechanisms are introduced [16]. Li et al. proposed an SSD based on the improved dual network for the images of insulators and spacers taken by UAVs [17], which realized the high-precision detection of electrical equipment. Aiming at the problem of different self-blast areas and complex backgrounds, He et al. proposed the Mina-Net based on YOLOv4, which fused shallow feature maps with more detailed texture information into the feature pyramids, and used improved squeeze-and-excitation networks (SENet) to calibrate the features of different levels [18]. Deng et al. proposed an improved YOLOv4 object detection algorithm based on the MobileNetv3 backbone and parametric rectified linear unit (PReLU) activation function and detected insulator defects through this lightweight model [19]. Xing and Chen processed images through Gaussian filtering, mosaic data enhancement, and k-means++ clustering and replaced the YOLOv4 backbone with MobileNet, which improved the detection speed and accuracy [20]. Li et al. reduced the negative impact of uneven lighting on YOLOv5-based insulator defect detection results through multiscale gradient-domain guided filtering and two-dimensional adaptive gamma transform [21]. Souza et al. proposed a hybrid YOLO model based on ResNet-18 and YOLOv5-X, which can detect faulty components in transmission lines by combining with a single UAV system [22]. Dai solved the uncertainty problem of insulator defect detection by applying a Gaussian function in front of the inspection head of YOLOX [23]. It can be seen that SDD, YOLOv4, YOLOv5, and YOLOX have all been used to detect defects and faults in transmission lines. In actual transmission line defect detection experiments, these methods have high requirements on image quality and cannot detect small-target insulators and defects in complex backgrounds, and the detection accuracy and efficiency of these methods need to be further improved.

Therefore, the existing defect detection methods for insulators of high-voltage lines are still difficult to meet the practical application requirements. The main reasons and research gaps are summarized as follows: (1) The transmission line passes through plateaus, mountains, valleys, etc., so the power inspection covers a wide range and the terrain and background are particularly complex. However, most of the existing transmission line defect detection methods based on a single UAV only detect insulator defects or bird's nests and the situation where multiple defects occur simultaneously is ignored. (2) Due to the influence of shooting angles, background noises, and lighting conditions, it is difficult to ensure the reliability of transmission line defect detection. In addition, the YOLOv4-based and YOLOv5-based detection methods cannot meet the requirements of precision and speed. (3) The existing defect detection methods for transmission lines only detect a single fault or defect, such as insulator self-blast, breakdown, or bird nest. The reasons for the abovementioned problems depend largely on the lack of image samples and the low quality of small samples. In the actual detection tasks, the same images or lens may contain multiple defects, which brings great challenges to the current transmission line fault detection.

In view of the abovementioned problems, we proposed a transmission line defect detection method based on YOLOv7 and the multi-UAV collaboration platform. The main contributions and innovations are shown in Figure 1.

(1) To address the problems of low efficiency and small search range caused by the existing research using only a single UAV to detect defects in transmission lines, we constructed a multi-UAV cooperation platform. Through the integration of the multi-UAV module, positioning module, path planning module,

and detection module, multi-UAV can not only plan flight paths autonomously through the control of the DJI mobile SDK module but also detect and locate defective components and positions through YOLOv7 and coordinate calibration. This platform can not only detect and locate defects well in transmission lines, but also flexibly connect several UAVs. Therefore, the proposed multi-UAV collaboration platform can not only increase the search range per unit time but also improve the defect detection reliability.

(2) In order to improve detection accuracy and efficiency as much as possible, we proposed a defect detection module based on YOLOv7, and it is used as a detector and integrated into the multi-UAV module through the DJI mobile SDK module. After detecting targets and defects on the transmission line, the actual location of the defects can be located through the corresponding relationship between the calibrated parameters and the coordinate system, and the problems of low accuracy caused by complex backgrounds, single UAV, and shooting lighting have been reduced.

(3) To comprehensively consider the types of defects in real transmission line scenarios, we built a transmission line defect detection dataset by combining web crawler datasets, public datasets, and live shooting datasets, which contains three types of most common transmission line defect images, including cracked insulators, insulator self-blast, and bird nests, and the problems of lack of data and low quality of samples have been solved.

The rest of this paper is arranged as follows. Materials and methods are described in Section 2, including the multi-UAV collaboration platform and the YOLOv7 detection algorithm. The results of the transmission line defect detection are analysed in Section 3. Some useful experimental analyses and conclusions are summarized in Section 4.

2. Transmission Line Defect Detection Method Based on YOLOv7

2.1. Multi-UAV Collaboration Platform. We proposed a multi-UAV collaboration platform, of which the multi-UAV module, positioning module, path planning module, and detection module are the most critical components. The multi-UAV module we built is an open interface platform, and several DJI UAVs can flexibly access the platform through the open interface. DJI-branded UAVs are not only cheap but also have good performance and high scalability. In the proposed multi-UAV module, an effective DJI mobile SDK module is used to control the flight of the UAVs, and the work of the pan tilt and camera is well coordinated. The DJI mobile SDK consists of six main parts, including gimbal, cameral, remote controller, airlink, light controller, and battery, which are inherited from DJIBase component. For each submodule, the most detailed feature descriptions are shown in Figure 2.

Then, we establish a suitable path-planning method for each UAV in the collaboration platform. The flight path planning method connected to the platform can be divided into two modes; one is to divide a global flight area based on the flight path and search range, and the other is to plan and receive the flight path and area of each UAV through map annotation. In this paper, we divide flight points and missions based on the actual situation and search scope of the transmission line, using map markers. First, the geographic coordinates that the UAVs on the transmission line need to reach are sequentially marked as array coordinates. Then, we plan specific flight point coordinates for each specific UAV, and all UAVs connected to the platform have corresponding paths and flight point coordinates. Under the control of the DJI mobile SDK, all UAVs within the collaboration platform fly according to preplanned flight paths, expanding the search range and improving search efficiency. The steps of the multi-UAV collaboration platform are as follows.

(1) Division of search area on transmission lines. We divide the search area of the 4 G or 5 G signal base station where the transmission line is located as a reference centre. First, we are centred on a 5 G signal base station and preliminarily determined by the UAV's maximum flight distance as the radius. In the divided search area, each UAV gradually shoots video along the transmission line from the inside out. When the range of each UAV is accurately determined, we can plan the specific flight path of each UAV based on the perspective of each UAV's camera and maximum flight distance. Generally speaking, those UAVs that can fly longer are allocated more grid search areas, while those UAVs with smaller camera fields are allocated to a higher flight path. In this way, the coordinated operation of multiple UAVs has greater security and reliability.

(2) Route planning for transmission line defect detection. Transmission lines often span a variety of different terrains, and the autonomous flight of UAVs is often affected by complex terrain. In order to display the high lines in real time in the map of the detection system, we embed a digital elevation model (DEM). We plan the aerial photography path of the UAVs between 20 m and 30 m above the contour line; the UAVs' lifting requirements have been reduced, and the efficiency of image collection has been improved.

(3) Marking of inspection areas. To avoid duplication and omissions in the inspection area of the transmission line as much as possible, we abstract the perspective of the UAVs' camera into a convex quadrilateral, and the search area of each UAV is visually marked. To solve the problem of discreteness between videos collected by multiple UAVs, we add each calculated polygon area to the polygons in the search area. Through the abovementioned methods, the same inspection area will neither be repeatedly photographed nor be missed or ignored.

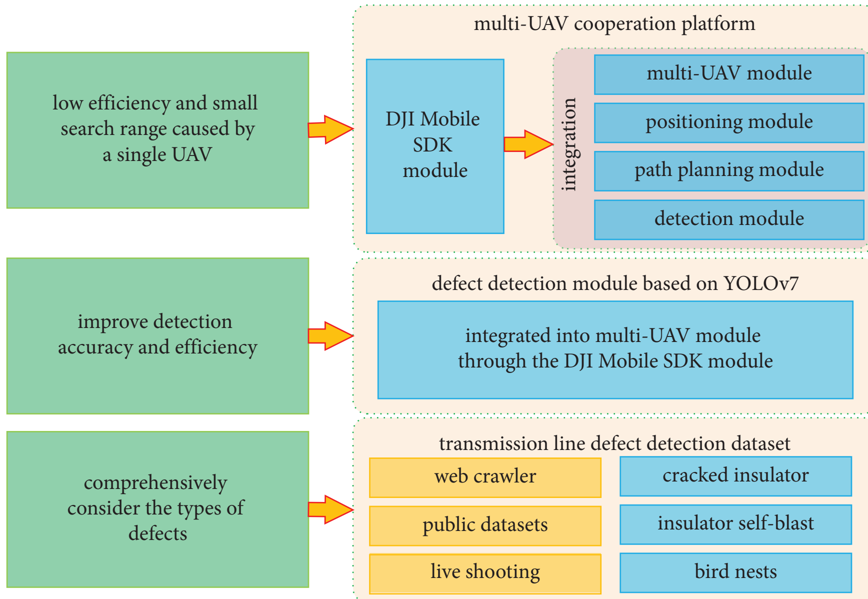


Figure 1: Main contributions and innovation points.

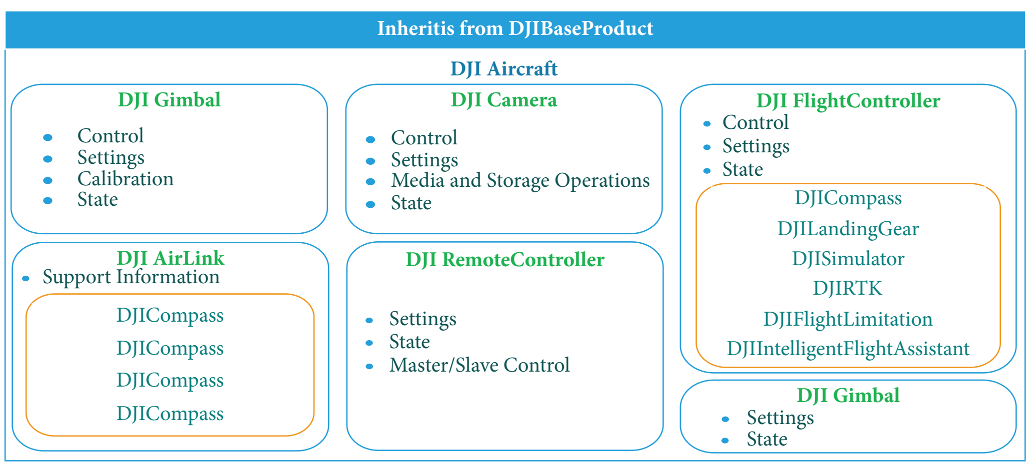


Figure 2: The DJI mobile SDK.

(4) Target positioning. With the embedded YOLOv7 detection model, device defects in transmission lines can be detected. However, how to locate the detected defects or the true location of the target is a key issue. The corresponding relationship between the WGS84 coordinate system and the pixel coordinate system can be obtained through the calibrated UAV parameters and the homologous video stream. More information can be found in our publication [24].

(5) Collaboration platform testing. To verify the effectiveness of the proposed collaboration platform, we build a simple coordination system by using two DJI Mavic 2 Pro UAVs, and the preliminary test results are shown in Figure 3.

We test the proposed method in Dajianshan, Kunming, and we first select the lowest contour line of Dajianshan as the flight path. As shown in Figure 3, the orange UAV flies clockwise from the start to the end along the orange-marked aerial route. At the same time, the purple UAV flies counterclockwise from the start to the end along the aerial shooting route marked in purple. In this way, video data from the area around this contour line are collected and saved by UAVs. After both UAVs reach the finish line, both UAVs fly to a second contour line at a higher level. The orange UAV then flies counterclockwise from the finish point to the start along the orange-marked aerial route. At the same time, the purple UAV flies clockwise from the endpoint to the starting point along the aerial photography

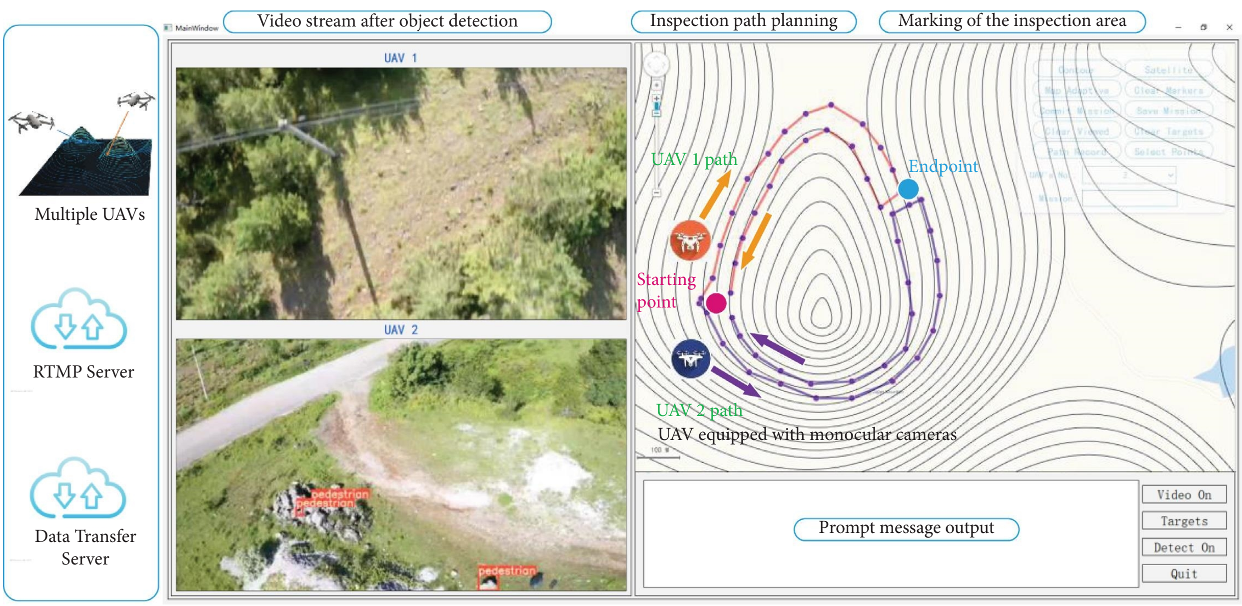


Figure 3: System structure.

route marked in purple. In this way, video data from the area near the second contour line are collected and saved by the UAVs. It is worth noting that the scope of UAV inspection has been significantly increased by this combination of horizontal and vertical path planning. After the two UAVs collect nonoverlapping video signals, the detection module obtains these video streams through real-time message protocol (RTMP) and data transmission servers and detects defects in the transmission line. As shown in “UAV1” and “UAV2” in Figure 3, the targets that appear in the videos collected by the two UAVs can be accurately detected by the YOLOv7 model, and the collaborative detection of multiple UAVs videos improves the efficiency and reliability of target detection.

As shown in Figure 3, the area near the two contour lines in Kunming’s Dajian mountain is completely inspected by two UAVs working together in real time. In fact, more than two UAVs can be embedded into our collaborative platform, the energy consumption requirements of a single UAV are reduced, and the search range and search efficiency are significantly improved. To sum up, some useful information about the multi-UAV collaboration platform can be summarized as follows.

(1) Normally, the same inspection range in Figure 3 requires a set of independent UAV to patrol twice along two different contour lines. Alternatively, two sets of independent UAVs patrol along two different contour lines once. In addition, independent inspection methods face the risk of overlapping inspection scopes. In the method proposed in this paper, two UAVs are integrated into a control system, and the implementation of inspection tasks is completed simultaneously, and there is no overlap in the inspection area. Detection and location of transmission line defects can be completed on a computer with low configuration and energy consumption and hardware requirements of the UAVs are further reduced.

(2) If a single UAV is adopted, the path planning method lacks flexibility, and some key points may be ignored or overlapping inspections may occur. Through the DEM-based path planning method, the effectiveness of multi-UAV path planning and the accuracy of target positioning have been improved to a certain extent. By capturing video streams from UAVs equipped with monocular cameras, the target positioning system can locate the target from the video stream to the world geographic system 1984. Therefore, through the multi-UAV collaborative system, the problems of omission and overlap in the inspection area, the accuracy of coordinate transformation, and defect localization can be solved to a certain extent.

(3) The speed of defect detection depends on the speed of image acquisition, the speed of image transmission, and the execution speed of the object detection algorithm. When the transmission rate is equal, the image acquisition speed based on multiple UAVs is faster than that based on a single UAV, and the object detection speed based on multiple video streams is faster than that based on the single video stream. From the experimental results, it can be seen that the speed of the defect detection module based on two UAVs in this paper is much greater than that of the defect detection module based on a single UAV. The accuracy of defect detection depends on the image quality and the performance of object detection algorithms. In our experiment, multiple UAVs can improve the quality of images by reducing omission and overlap issues, thus invisibly

improving the accuracy of defect detection. In addition, many literatures have proven that YOLOv7 is a fast and accurate detection algorithm, so the experiments in this article achieved the expected detection performance compared to methods such as YOLOv5 under the same parameters and structure.

2.2. YOLOv7-Based Defect Detection Method. The accuracy of defect detection is a prerequisite for defect location. To meet the accuracy and real-time requirements of defect detection, we choose the newly released YOLOv7, which includes input, backbone, neck, and prediction, and it is currently the fastest detector with the highest accuracy. The several improvements of YOLOv7 can be summarized as follows.

(1) Extended efficient layer aggregation networks: In YOLOv7, the author proposed an extended-efficient long-range attention network (E-ELAN), which can converge more effectively by controlling the shortest longest gradient path. The main architecture of E-ELAN is shown in Figure 4. The E-ELAN enhances the learning ability of the network through expansion, shuffle, and merge cardinality without damaging the original gradient path. Through the group convolution strategy in E-ELAN, the channels of computational blocks are expanded, and the same channel multiplier and group parameter are used for all the computational blocks.

(2) Model scaling: For the concatenation-based model, we cannot analyse the effects of different scale factors on the amount of parameters and computation separately. In YOLOv7, a corresponding compound model scaling method is proposed. When we scale the depth factor of a computational block, the change in the output channel of the block should also be calculated. Then, the width factor scaling with the same amount of change on the transition layers can be performed. The compound scaling up depth and width for the concatenation-based model is shown in Figure 5. When the model is scaled, only the depth the computational block needs to be scaled, and the remaining of the transmission layer performs the corresponding width scaling.

(3) Planned reparameterized convolution: In view of the problem that RepConv reduces the detection accuracy, the authors design planned reparameterized convolution in YOLOv7. By analysing the combination of RepConv and different structures, we find that the RepConv provides more diversity of gradients for different feature maps. In YOLOv7, RepConvN is used to design the planned reparameterized convolution; an example is shown in Figure 6.

(4) Coarse for auxiliary and fine for lead loss: Deep supervision improves the performance of the model. For the issue of label assignment, researchers use the quality and distribution of the prediction output and consider with the ground truth to generate a reliable soft label. YOLO uses the IOU between the prediction bounding box and the ground truth as the soft label of the object. As shown in Figure 7, the lead head guided label assigner is based on the prediction result of the lead head and the ground truth. The lead head has a strong learning capability, so the strategy should be more representative of the distribution and correlation between the data and the target. Coarse-to-fine lead head-guided label assigner generate the coarse label and fine label, where the fine label is the same as the former and the coarse label is generated by allowing more grids to be treated as the positive target. To avoid losing target information, we will focus on optimizing the recall of auxiliary heads in the object detection task.

3. Transmission Line Defect Detection Results and Analysis

3.1. Experimental Preparation. To verify the real time and effectiveness of the proposed defect detection method based on YOLOv7, we evaluated the detection performance of various inspection methods through a series of experiments. As shown in Table 1, we analyse the experimental results and verify the effectiveness of the method through the hardware and software configurations in the following.

In this paper, two methods are used to collect transmission line defect datasets, crawling insulator images on the network through web crawlers and taking insulator images of transmission lines in the Yuxi section of Yunnan power grid, and then the data enhancement method is used to optimize the datasets. Finally, a comprehensive dataset consisting of five types of transmission line defect images, including normal glass insulators, normal ceramic insulators, insulator self-blast, cracked insulator, and bird nests, is obtained, which contained a total of 4835 images. There are significant differences in the shooting angle, lighting, and image background of defect targets on these transmission lines, and the background and size transformation of defect targets are particularly complex in most images, as shown in Figure 8. It is thus clear that the complex backgrounds and size transformation bring great difficulties and challenges to the research of transmission line defect detection. Therefore, we divide 4835 images into training sets and test sets according to the ratio of 8 : 2 and propose a multi-UAV collaboration platform based on YOLOv7 to improve the accuracy and efficiency of transmission line defect detection in complex backgrounds.

3.2. Evaluation Methods. We compare and analyse various defect detection algorithms through evaluation indicators such as precision (P), recall (R), $F1$ score ($F1$), mean average precision (mAP), model size and speed, and the detection accuracy, generalization performance, computing efficiency, and storage size of the algorithms are well compared and analysed. Several key evaluation indicators are listed in the following:

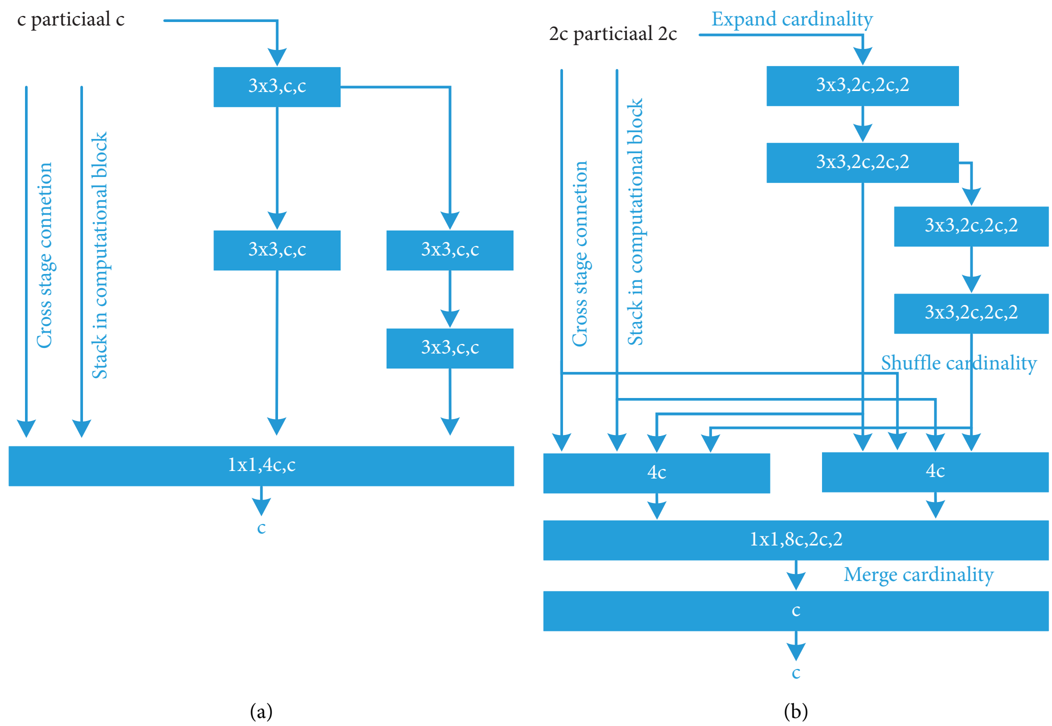


Figure 4: The structures of (a) ELAN and (b) E-ELAN.

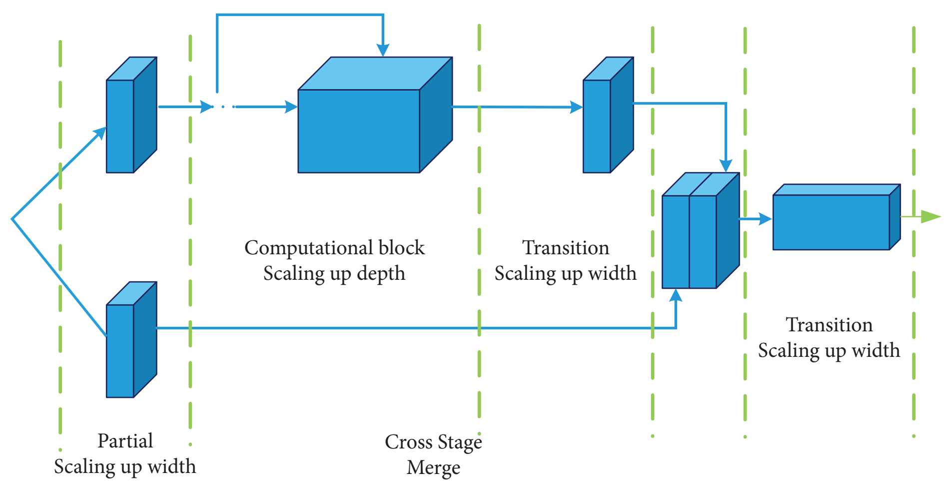


Figure 5: The compound scaling up depth and width for the concatenation-based model.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}},$$
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}},$$
$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}, \tag{1}$$
$$\text{AP} = \int_0^1 P(R)\text{dR},$$

where TP, FP, and FN represent true positive, false positive, and false negative, respectively. The closer $F1$ is to 1, the better the detection accuracy and generalization performance of the model. Average precision (AP) is a definite integral, which can be represented by the closed interval of the precision recall curve. In addition to the above 4 equations, the average recognition precisions of all defect categories in transmission lines can be represented by mAP.

$$\text{mAP} = \frac{\sum_{i=1}^{K} AP_i}{K}, \tag{2}$$

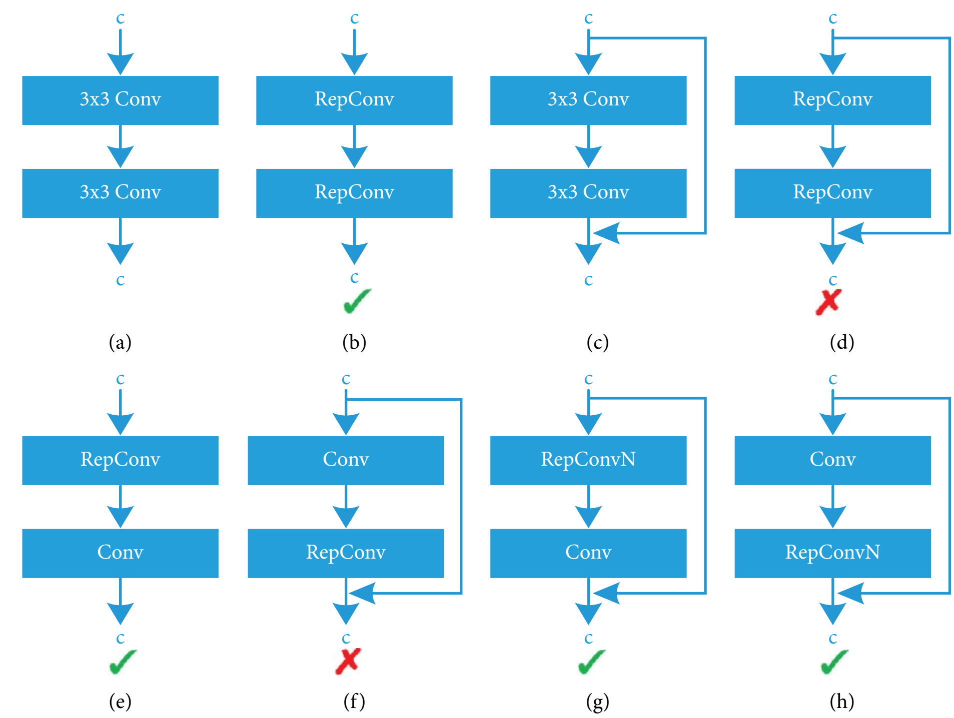


FIGURE 6: Planned reparameterized model. (a) PlainNet. (b) RepPlainNet. (c) ResNet. (d) RepResNet. (e) P1-RepResNet. (f) P2-RepResNet. (g) P3-RepResNet. (h) P4-RepResNet.

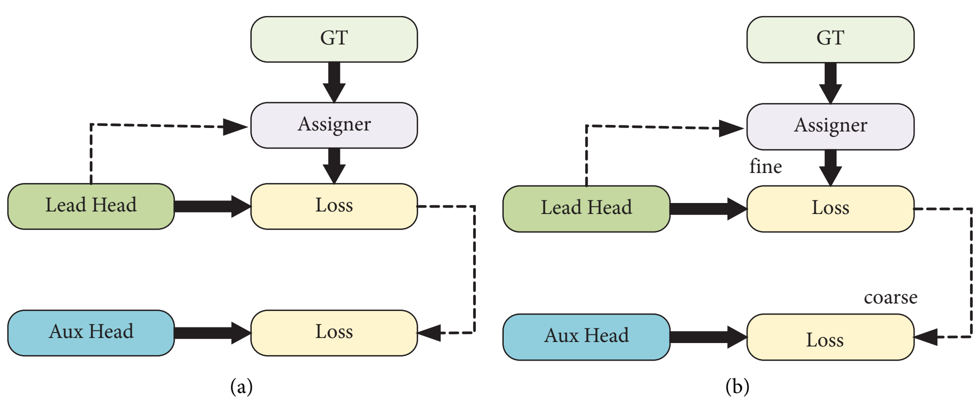


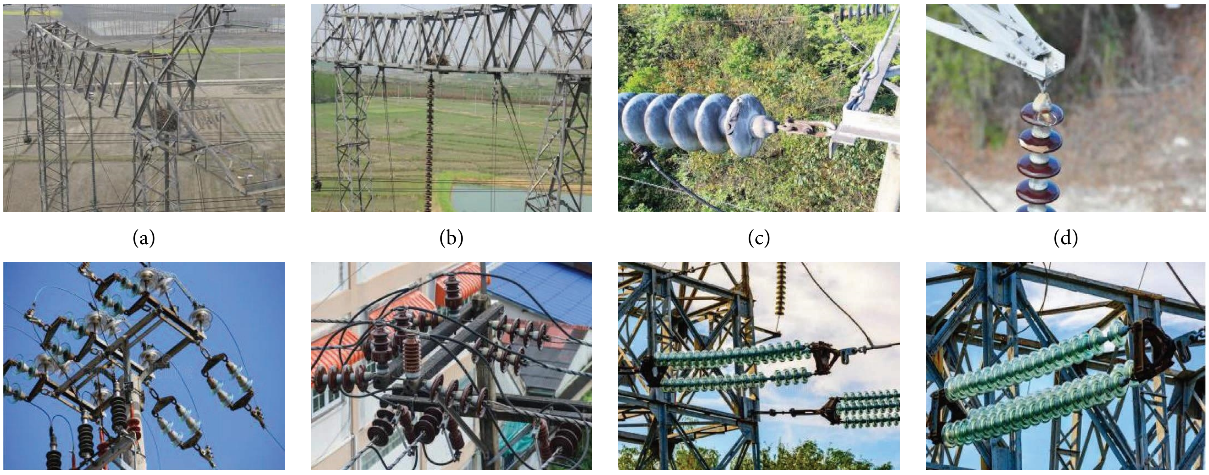
FIGURE 7: Coarse for auxiliary and fine for lead head label assigner. (a) Lead guided assigner. (b) Coarse-to-fine lead guided assigner.

TABLE 1: Experimental environment.

Parameters	Configurations
GPU	Nvidia GeForce GTX 2080Ti (24 G)
CPU	Intel Core i7-10700F, RAM 32 GB, CPU 2.90 GHz
Operating system	Ubuntu 18.04
Visual studio system	Python 3.6, Pytorch1.7.1
Accelerated environment	cuDNN8.0.5, CUDA 11.1

where K represents the total class of the target sample, AP_i represents the detection accuracy of the model for the type i sample, and mAP represents the average detection accuracy of the model for all class samples, i.e., the average of all APs.

In addition, the storage size of the trained model can be expressed as "size," and the sum of preprocessing time, nonmaximum suppression time, and inference time can be expressed as "speed."



(a) (b) (c) (d)

(e) (f) (g) (h)

FIGURE 8: Transmission line defects in different backgrounds. (a, b) Bird nest. (c, d) Cracked insulator. (e) Normal glass insulator. (f) Normal ceramic insulator. (g, h) Insulator self-blast.

3.3. Comparison of Parameters in Training. The datasets obtained by the multi-UAV collaboration platform and data enhancement processing greatly expand the number of datasets, and then we train 5 state-of-the-art YOLO-based defect detection algorithms through the obtained datasets. In order to ensure the comparability and fairness of experimental results, all datasets, parameters, and experimental environments are the same, and the detection performance of YOLOv5-S, YOLOv5-X, YOLOv7-Tiny, YOLOv7-X, and YOLOv7 on defective targets is fully released. The training parameters are shown in Table 2.

Figure 9(a) clearly shows that the training precision curves of almost all detection models converge to a fixed value after 300 epochs. Specifically, YOLOv7 converges to the highest training accuracy after 240 epochs. The training precision curves of YOLOv5-X and YOLOv7 are not only smoother but also have higher training convergence precision and faster convergence speed. At the end of the training, YOLOv7 achieved the highest precision, indicating that YOLOv7 has the best convergence speed and convergence accuracy compared to other methods. As shown in Figure 9(b), the recall curve obtained by YOLOv7 not only has the fastest convergence speed, convergence occurs after 200 epochs, but also has the largest recall value and the highest smoothness. The experimental comparison results show that the precision curve and the recall curve obtained from YOLOv7 in the training phase have the fastest convergence speed and the highest convergence accuracy, indicating that the trained YOLOv7 model has better performance than the other versions of YOLOv5 and YOLOv7. In addition, the smoothness of the precision and recall curves of the YOLOv7 model is the best, indicating that YOLOv7 has the best robustness to defect samples in transmission lines.

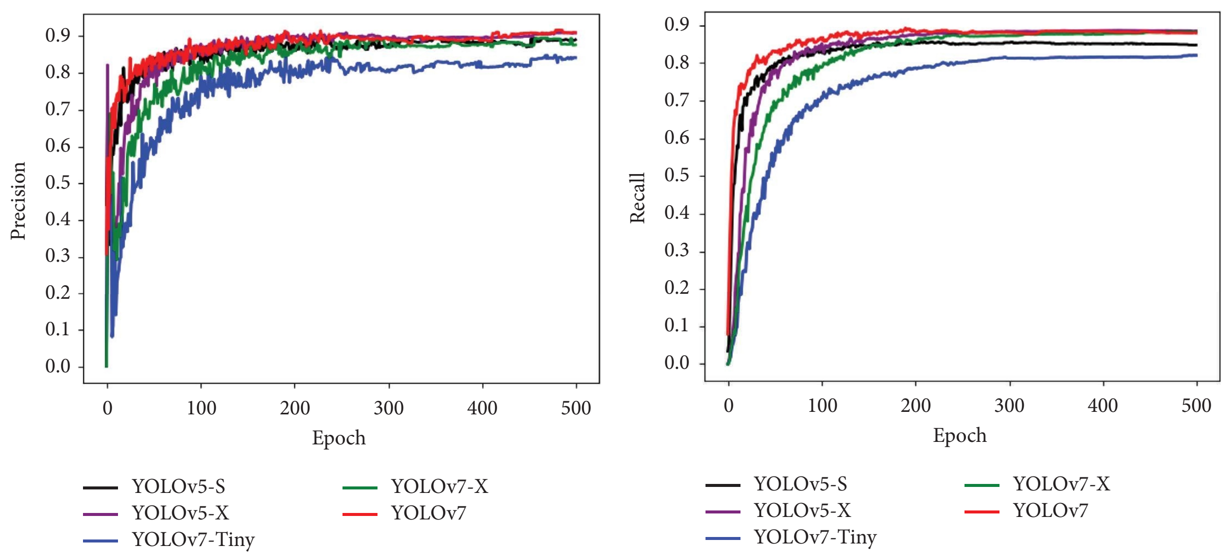
3.4. Test Performance Comparison. We tested these trained models through 1101 real scene images from the proposed transmission line defect datasets, in which the threshold for IOU is 0.7. The precision (P) and recall (R) of the five transmission line defect detections, including normal glass insulator, normal ceramic insulator, cracked insulator, insulator self-blast, and bird nest, are shown in Table 3. Compared with normal insulators, there are fewer images and cases of bird nests, insulator self-blast, and cracked insulator. In the three fault cases, the detection of the insulator self-blast is the most difficult, and the detection difficulty of the cracked insulator is only second to the insulator self-blast. YOLOv7-X obtained the best precision in bird nest, insulator self-blast, and cracked insulator defect detection, and YOLOv7 achieved the second highest detection accuracy among these types of defect samples. YOLOv7 received the best recall in four types of defect detection except insulator self-blast. In real transmission line defect detection experiments, YOLOv7 obtained the best precision (P) and recall (R) in almost all categories of defect object detection. Compared with the YOLOv5 and YOLOv7 series, YOLOv7 have better performance for insulator defect detection in complex backgrounds.

To compare these transmission line defect detection models more comprehensively and verify the high efficiency and low complexity of the YOLOv7-based transmission line defect detection models, we provide the precision (P), recall (R), mAP, $F1$-scores, speed, and size obtained from these models in the test phase, as shown in Table 4. It should be noted that the test environment and hardware devices of various models are shown in Table 1, and the test set contains 1101 images in real scenarios, of which the threshold value of the IOU is 0.7, and the other common parameters and working conditions of the model are the same. The reason why different models are tested with the same hardware environment, model parameters, and working conditions is to ensure the fairness and effectiveness of model performance comparison.

As shown in Table 4, YOLOv5-X achieved the highest precision 0.893 and the best $F1$ score 0.877, YOLOv7 achieved the highest recall 0.868 and highest mAP 0.886, and

Table 2: Training parameters.

Batch size	Size	Epochs	Learning rate	Gamma	Weight decay	Momentum
8	640 ∗ 640	500	$1e-5$	1.5	0.001	0.98



(a) (b)

Figure 9: Comparison of precision and recall during training. (a) Precision curves. (b) Recall curves.

Table 3: The precision (P) and recall (R) for defects detection.

Classes	Labels	YOLOv5-S		YOLOv5-X		YOLOv7-Tiny		YOLOv7-X		YOLOv7	
		P	R	P	R	P	R	P	R	P	R
birdNest	131	0.901	0.907	0.901	0.905	0.876	0.923	0.906	0.893	0.903	0.924
Cracked	467	0.864	0.833	0.876	0.859	0.818	0.794	0.891	0.844	0.88	0.863
normalCeramic	4841	0.867	0.764	0.907	0.83	0.83	0.673	0.881	0.783	0.874	0.842
normalGlass	1803	0.888	0.734	0.918	0.784	0.79	0.702	0.895	0.743	0.908	0.788
selfBlast	271	0.851	0.889	0.864	0.934	0.864	0.889	0.872	0.952	0.865	0.926

Table 4: Transmission line defect detection results obtained by different methods.

Models	P	R	mAP	$F1$	Speed (ms)	Size (Mb)
YOLOv5-S	0.874	0.825	0.845	0.848	1.9	13.7
YOLOv5-X	0.893	0.862	0.878	0.877	10.3	166
YOLOv7-Tiny	0.836	0.796	0.821	0.815	1.2	11.7
YOLOv7-X	0.889	0.843	0.883	0.865	6.3	135
YOLOv7	0.886	0.868	0.886	0.876	6.2	71.3

YOLOv7-Tiny has the fastest speed 1.2 ms and smallest size 11.7 Mb, which indicates that YOLOv7 and YOLOv5-X are more suitable for offline detection or servers that require higher transmission line defect detection accuracy and YOLOv7-Tiny is more suitable for online monitoring or embedded devices that require higher detection speed and smaller model size. In addition to YOLOv7 and YOLOv5-X, YOLOv5-S and YOLOv7-X also achieved good results on various evaluation indicators. Compared with other detection models, the recall, mAP, and $F1$ indicators obtained from YOLOv7 all achieved the best values, while precision, speed, and size all ranked third and had a small difference from the top two. That is, YOLOv7 achieved the best performance in the most critical indicators and also ranked among the top in other indicators, and the accuracy and speed of defect detection meet the actual needs. According to the actual situation of transmission line defect detection scenarios, YOLOv7 undoubtedly achieved the best performance in comprehensive evaluation and is, therefore, the best candidate to be added as a detector to the multi-UAV collaboration platform.

To demonstrate the performance of various models in real transmission line defect detection more intuitively, the detection results of each type of defects obtained by the five defect detection methods are shown in Figure 10. For the cracked insulator, the five models have successfully detected two cracked insulators and other normal ceramic insulators; YOLOv7 received the highest confidence, with YOLOv5-X coming in second. For the normal insulator, YOLOv7 has

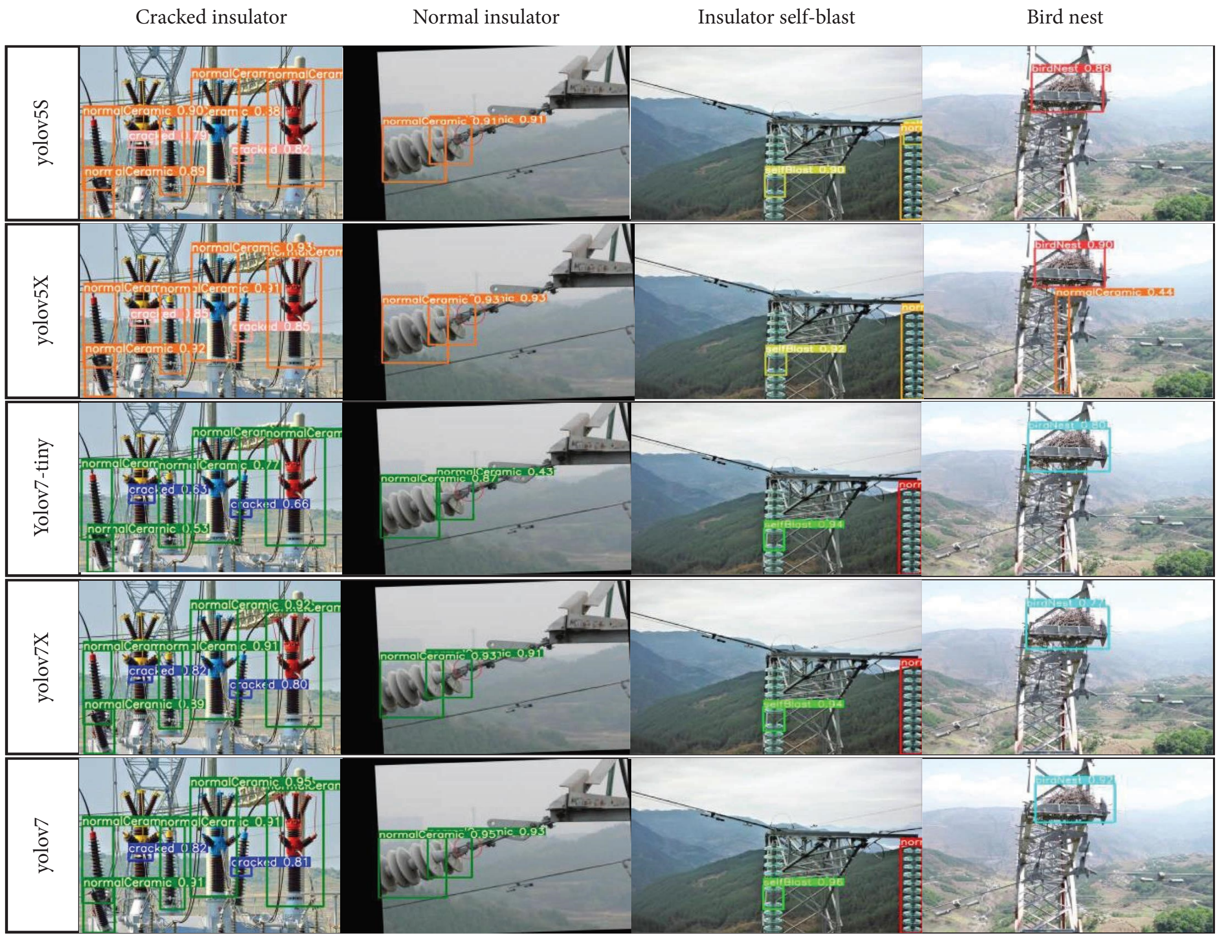


Figure 10: Comparison of detection effects of different models.

the highest confidence and the next is YOLOv5-X. In the insulator self-blast and bird nest images, YOLOv7 received the highest confidence, and YOLOv5-S and YOLOv5-X have error detection. The results show that YOLOv7 is more accurate than the existing YOLOv5 and some YOLOv7-based models in defect detection under complex backgrounds, and several improvements to YOLOv7 are effective. From four different types of defect detection results, YOLOv7 achieved the best confidence, and there are no cases of missed detection or false detection. The practical results and various evaluation indicators achieved by YOLOv7 demonstrate the high superiority of the transmission line defect detection method based on YOLOv7. Therefore, it is introduced into a multi-UAV collaborative system to detect various defects in transmission lines.

3.5. Transmission Line Defect Detection Results. It can be seen from the comparative experiments of training and testing that YOLOv7 has the highest precision and recall in training, YOLOv7 achieved the best recall and mAP in testing, and YOLOv5-X has the highest precision and $F1$ score. In terms of time, YOLOv7-Tiny got the fastest speed in training and testing. Transmission line defect detection is critical to the safety of transmission lines and personnel, and it places particular demands on precision. Therefore, we use the YOLOv7 model to detect transmission line defects in various scenarios in the real world, and the testing performance is shown in Table 5.

Table 5: Transmission line defect detection results.

Classes	Labels	P	R	mAP	$F1$
birdNest	131	0.903	0.923	0.915	0.912
Cracked	467	0.88	0.863	0.893	0.871
normalCeramic	4841	0.874	0.842	0.864	0.857
normalGlass	1803	0.908	0.788	0.848	0.843
selfBlast	271	0.865	0.926	0.911	0.894
All	7513	0.886	0.868	0.886	0.876

For insulator self-blast and cracked insulator faults with few samples and high identification difficulty, YOLOv7 has made good breakthroughs in the four evaluation indicators, and several improvements of YOLOv7 are significant. For “birdNest,” which has the smallest sample, the YOLOv7-based method obtains the best mAP 0.915 and the best $F1$ 0.912, respectively. In addition, for “selfBlast” with fewer samples, the YOLOv7-based method obtains the best recall 0.926 and other indicators are also very impressive, indicating that the YOLOv7-based detection model has good generalization performance for small samples and unbalanced samples. Overall, the detection model based on YOLOv7 achieved a precision of 0.886 and recall of 0.868 on

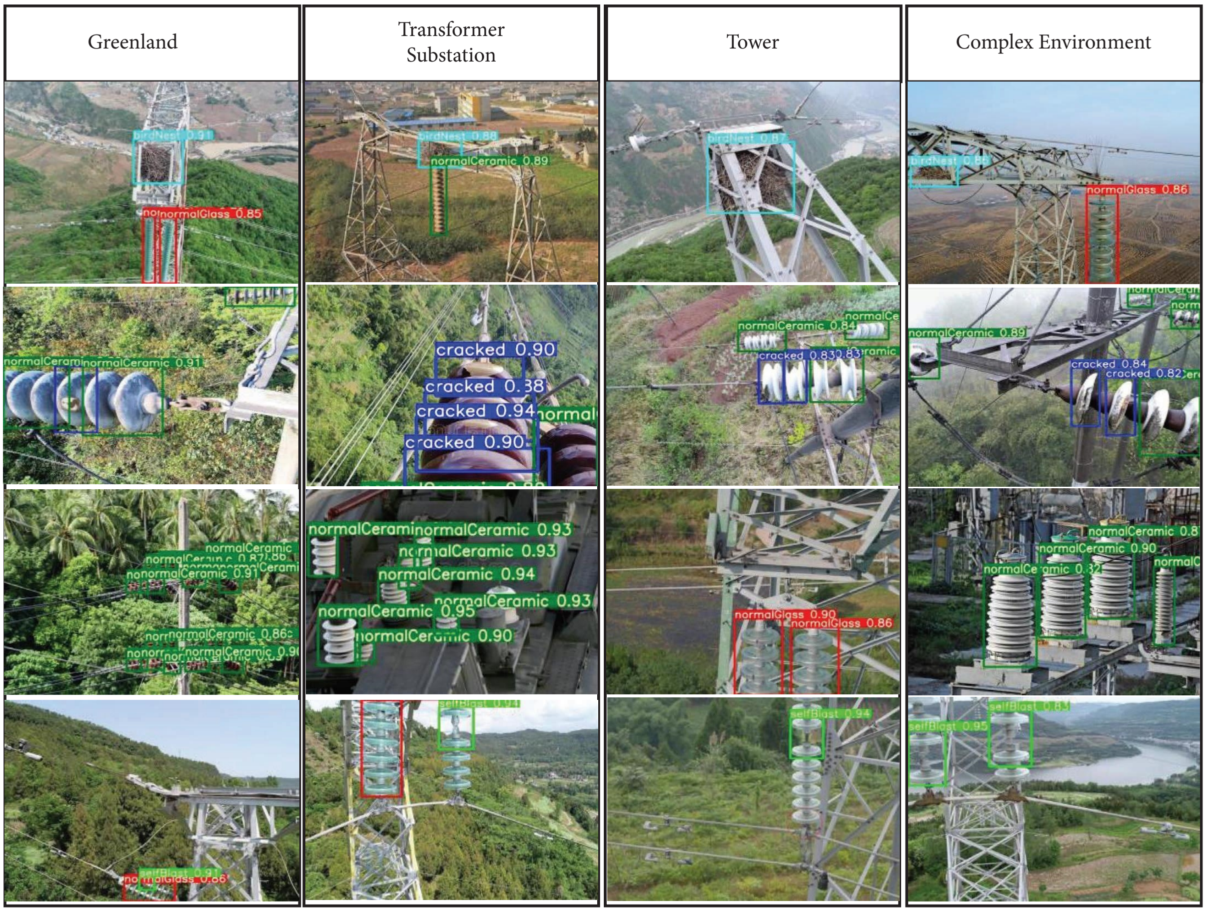


Figure 11: Detection performance testing of proposed methods in different real scenarios.

all samples, which can meet the actual needs of transmission line defect detection.

According to different environments in actual transmission line inspection and insulator defect detection, we divide the test dataset into four most common scenarios, including green land, transformer substation, high-voltage tower, and other complex environment, as shown in Figure 11. “Greenland” means that the background of the picture is a green space. “Transformer substation” means that the image data are collected from the substation or the picture contains the background of the substation. “Tower” refers to the high-pressure tower in the background of the image. “Complex environment” refers to images collected from extreme weather such as foggy or rainy days or poor image quality. The size, illumination, shooting angle, and image background of transmission line defect images in different real scenes are quite different, and many defect detection methods are difficult to achieve satisfactory results. However, the YOLOv7 model we trained can successfully detect the five most common transmission line defects in four different complex scenarios, and has achieved very good performance in each type of defect detection; the confidence has reached the practical application requirements. In “Greenland,” the proposed method accurately detects bird nest, normal glass insulator, normal ceramic insulator, and insulator self-blast, with confidence levels ranging from 0.85 to 0.91. In “Transformer substation” and “Tower,” the proposed method accurately detected all defect targets that appeared, with confidence levels ranging from 0.83 to 0.95. Even in the “Complex environment” with low image quality, missed detection, and false detection did not occur, with confidence levels ranging from 0.82 to 0.95. In addition, we also test and analyse the transmission line defect dataset constructed based on real scenarios through the multi-UAV collaborative platform and YOLOv7 model, and the detection time of a single image is 6.5 ms and the detection accuracy is very high, and the results show that the proposed defect detection method can ensure the detection accuracy and detection efficiency of multiple video streams.

4. Conclusion

A transmission line defect detection method based on YOLOv7 and the multi-UAV collaboration platform is proposed. Multiple UAVs can flexibly access the collaborative platform through the same control system. The practical results indicate that the multi-UAV collaboration platform can patrol a wider range within the same time and can effectively avoid path omissions and overlap issues, which improve the efficiency and reliability of inspection. Second, several improvements of YOLOv7 have effectively improved the error detection problem caused by the aerial shooting angle, changing lighting, and complex background. Compared with the detection results obtained by YOLOv5-S, the YOLOv7-based defect detection method improves accuracy by 1.2%, recall by 4.3%, and mAP by 4.1%. Compared with other detection models, the recall 0.868, mAP 0.886, and *F*1 0.876 obtained from YOLOv7 all achieved the best values, while precision 0.886, speed 6.2 ms, and size 71.3 Mb all ranked third and had a small difference from the top two. The proposed defect detection method based on YOLOv7 has undoubtedly achieved the best results in experimental and comprehensive evaluation, meeting the accuracy, speed, and size requirements for various defect detections in transmission lines. The defect detection dataset we proposed covers almost all the most common defect types such as normal insulators, insulator self-blast, cracked insulator, and bird nests, and more types of transmission line defect images can be added to this dataset. By expanding the dataset, our proposed method can simultaneously detect multiple defects in transmission lines, without being limited to single defects or certain defects, and the detection efficiency and reliability are improved. In addition, the defect detection method proposed by us has a high level of automation and intelligence, and the labor intensity of transmission line inspectors is reduced and the safety is further improved. However, the flight path of multiple UAVs is set in advance according to the contour line, and the image data collected by the system in the undulating areas of the Yunnan Plateau have the problem of omission, overlap, or low quality. Therefore, in the near future, we will study how to make the collaborative system have the functions of autonomously planning paths and dynamically adjusting paths. At the same time, the YOLOv7 detection algorithm is difficult to detect low-quality small targets caused by altitude changes, extreme weather, and object occlusion, so we will study more accurate and faster object detection algorithms and embed the algorithm into multi-UAVs through embedded devices to improve the accuracy and speed of defect detection.

Abbreviations

UAV:	Unmanned aerial vehicle
YOLO:	You only look once
ECA-Net:	Efficient channel attention module
CNN:	Convolutional neural network
R-CNN:	Region-based convolutional neural network
Faster R-CNN:	Faster region-based convolutional neural network
CenterNet:	Objects as points
CBAM:	Convolutional block attention module
ResNet:	Residual network
SSD:	Single shot detector
RPN:	Regional proposal network
SENet:	Squeeze-and-excitation networks
PReLU:	Parametric rectified linear unit
DJI:	DJ Innovations
DEM:	Digital elevation model
RTMP:	Real-time message protocol
E-ELAN:	Extended-efficient long-range attention network
P:	Precision
R:	Recall
*F*1:	*F*1 score
Map:	Mean average precision.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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