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Research On Infrared Fault Detection Of Substation Equipment Based On Deep Learning

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Abstract:
The reliable operation of power systems cannot be achieved without efficient and precise operation and maintenance methods. Based on the problems existing in actual operation and maintenance, and starting from the demand orientation, this paper focuses on the characteristics of low efficiency, reliance on judgment experience, and uncertainty of manual inspection in substations, and proposes a target detection method based on deep learning and YOLOv7. This method is an improvement on the traditional target detection. Through ablation and comparison experiments, the improved model can enhance detection accuracy, reduce the network model, and increase detection speed compared with the traditional model.

Background: *As an important networking component in the operation of the power grid, substations can achieve the conversion between different voltage levels and the distribution of loads. Undoubtedly, they play a crucial role in the safety of the power grid and the reliability of power supply. However, with the aging of substation equipment and the reduction of its service life, the failure rate of the equipment gradually increases, intensifying the difficulty of substation maintenance work. In addition, as most of the main grid equipment in substations is set outdoors and located in complex urban environments or remote rural areas, the difficulty of fault handling is even greater, which brings great pressure and safety hazards to power enterprises. Conducting regular inspections of substation equipment as well as periodic and special safeguard inspections is an important means to ensure that power grid enterprises have the ability to issue risk warnings and eliminate risks in advance. Therefore, how to detect the faults and defects of substation equipment as early as possible to prevent substation accidents in advance has become a focus of attention in the power industry.*

Materials and methods: *By conducting infrared photography of the operating equipment in the substation, and then preliminarily processing the data for data augmentation and classification, an infrared detection dataset for the substation was created. The object detection method of YOLOv7 is adopted. Firstly, the GhostNetV2 module is introduced to conduct a lightweight design for the feature extraction backbone of YOLOv7. Aiming at the problem of insufficient fusion of the feature layer of the YOLOv7 algorithm model, the bidirectional Feature Pyramid Network (BiFPN) feature fusion module is introduced to improve the detection accuracy. Then, the loss function of YOLOv7 is replaced with the SIOU loss function to achieve dynamic adjustment of the regression loss of the model prediction box, thereby accelerating the convergence speed. And it plays a role in improving the recognition accuracy of the model. Finally, the model was experimented on the infrared detection dataset of the substation and compared with the mainstream methods to verify the effectiveness of the method in this chapter.*

Result: *The experimental results show that the substation infrared image defect detection model designed in this chapter has a 2.3% improvement in detection accuracy compared to YOLOv7, while the model size is reduced* *by 32%. When the model size is basically the same as that of YOLOv8m, the detection accuracy is increased by 4% and the detection speed by 43%. It can be concluded from this that the improved YOLOv7 model has achieved relatively ideal improvements in both defect detection accuracy and detection speed.*

Keywords: *Substation inspection Data augmentation Bidirectional feature pyramid network "Lightweight; Defect detection.*

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I. Introduction

Substation[1] inspection is an important part of the operation and maintenance of the power system and an important means to prevent power system faults. The inspection within the substation is mainly divided into regular routine inspection and special inspection based on the frequency arrangement. Among them, regular inspection mainly involves periodic checks of electrical equipment such as main transformers, knife switches, and switches within the substation, identifying relevant hazards and recording them for reporting to the operation and maintenance work area for handling.

At present, the inspection methods for electrical equipment in substations are mostly based on manual inspection. The traditional inspection methods mainly rely on visual inspection, auditory judgment and experience judgment. Due to the remote location of substations and the large amount of inspection work, 24-hour online monitoring cannot be achieved. The traditional inspection method uses infrared instrument equipment to measure temperature and screen for equipment with abnormal heating. There are a large number of substations in each region, and manual inspection work is the most arduous. Moreover, traditional manual inspection is closely related to whether the inspection workers' work is in place and whether the weather is convenient for inspection. During the high-load period of summer (winter) every year, there are always electrical equipment that are urgently shut down due to defects that have not been discovered and dealt with in time.

In recent years, with the advancement of technology and the application of artificial intelligence, the inspection of electrical equipment in substations has been developing towards intelligence[2], precision and efficiency. Relevant scholars have also been constantly innovating technical means to solve the above problems.

Traditional infrared image processing methods all first capture infrared images of substation equipment, then perform edge processing on the images. By improving the model, the complexity of the model is reduced, the recognition accuracy is enhanced, and the model is made lightweight and recognition efficient. A Representative achievement is Zhong Zhiming's improvement of the feature extraction module based on YOLOv7[3] to enhance detection speed, and then introducing a convolutional attention mechanism module into the YOLOv7 network to improve the network's detection accuracy.Representative achievements include Zheng Xiang et al. 's proposal of a multi-feature fusion method combined[4] with an improved support vector machine diagnostic approach, which fuses color features, edge features, and texture features, and optimizes the parameters of the support vector machine (penalty factor and kernel parameters) through an improved imperial competition algorithm. Representative achievements include the improved lightweight YOLOv7 method proposed by Chen Haibo et al., which introduced a high-resolution P2 detection head to enhance the detection of small targets. The parametr-free attention module SimAM can better extract the target features of different power transformation equipment in complex infrared backgrounds. The CARAFE module reduces the loss of feature information during the upsampling process. Further enhance the robustness of the algorithm.

With the rapid development of artificial intelligence, the application research of deep learning in the inspection and patrol of substation equipment will become an important technological breakthrough point of artificial intelligence. The main research ideas of methods based on deep learning are as follows. Representative achievements include that Xiao Tianlong et al. proposed a detection technology based on the improved YOLO 7th[5] edition algorithm, introducing an improved cross-stage partial network ghost version 3 module to replace the extended efficient layer aggregation network module in the head network, optimizing the network structure, and integrating a lightweight normalized attention module into the backbone network to enhance the utilization efficiency of infrared image features. Representative achievements include Li Xuqing's research and construction of a lightweight deep learning infrared image detection algorithm for power equipment that can be deployed on edge devices, and the deployment of this algorithm on edge computing devices to achieve intelligent detection of power equipment with real-time performance and accuracy. Representative achievements include Zhu Hongyu's improvement and training of the deep learning object detection algorithm YOLOv5[6], proposing an intelligent fault detection algorithm for substation equipment based on deep learning. This algorithm can identify various fault situations based on the appearance information of substation equipment, and simultaneously re-cluster the prior boxes using the K-means ++ algorithm. Make the network more suitable for the fault data set studied in this paper; Representative achievements include Lu Ling et al. proposing an improved YOLOv8 model checking method, which introduces a CA attention mechanism module, enhancing the feature extraction and feature fusion capabilities of the network model. The original model loss function CIoU is improved to SIoU to reduce the model's misjudgment rate. Representative achievements such as Yu Hong et al. proposed the equipment recognition of the Faster R-CNN algorithm[7], which conducts target recognition for six types of substation equipment to achieve precise positioning. Meanwhile, the actual labels of the input samples are obtained based on the algorithm of sparse Representation Classification (SRC). Representative achievements include that Zhang Jiayu et al. proposed an improved CenterNet_PRO[8] object detection algorithm model based on CenterNet, which adopted ShuffleNet V1/V2 as the backbone network and introduced FPN to extract multi-scale features. The surface temperature of power equipment was extracted and analyzed through the threshold segmentation method. Design and formulate the norms for judging temperature defects in power equipment and the temperature warning thresholds.

Due to the wide variety of electrical equipment in substations and the unstable heat generation points, the collected infrared images have the characteristics of similar colors, similar environments and backgrounds. However, the above-mentioned substation equipment inspection methods based on deep learning still have many situations of model complexity, errors and inaccurate positioning in practice, and there is still room for technical improvement.

II. Materials And Methods

Research period: December 2023 to August 2025.

Sample size: The inspection images were divided into normal sample sets and defect sample sets, and 8,407 and 6,960 infrared images were respectively screened out.

Experimental environment: The experimental software environment for the model in this chapter is Windows10 system, the programming language is Pycharm 2020.1.3, the deep learning framework is Pytorch1.9.0, and the CUDA version is 11.1.

The model training parameters are as follows: The Adam optimizer is used to update the model parameters. The initial learning rate (lr) is 0.01, the batch size of images is 8, the image size is 640×640, and the number of categories is 6.

Evaluation index: This study adopts accuracy (precision, P), recall (recall, R), mean average precision (mAP50), Parameters (Parameters), floating-point operations (FLOPs), frames per second (FPS), and model Weights (Weights) as the evaluation indicators of model performance. In the experiment, the intersection and union ratio (IOU) threshold between the predicted box and the real box was set at 0.5 as the criterion for judging the experimental results. These indicators can accurately understand the performance of the model in defect detection, and the indicators can be compared and optimized in the experiment.

Procedure methodology:

Ablation experiment:Based on YOLOv7, GhostNetV2, BIFPN and SIOU modules, which are more suitable for substation defect detection tasks, were integrated into the backbone network. The influence of different modules on the model detection effect was systematically studied through the ablation experiment. By analyzing the performance of different modules in various aspects such as P and R, the performance advantages of this algorithm were verified.

Comparative experiment:To verify the comprehensive performance of the improved YOLOv7 algorithm, this paper conducts a series of comparative experiments involving different types of object detection algorithms. Including the classic algorithm Faster R-CNN[9] in the Two-Stage detector, the classic algorithm SSD[10] in the One-Stage detector, DETR based on Transformer, and various YOLO series algorithms Including models such as YOLOv3, YOLOv5s, YOLOX-s, YOLOv7, and YOLOv8m. The model was trained and tested under the same dataset and with unchanged hyperparameters, verifying the advantages of the improved algorithm.

III. Algorithm And Model Design

YOLOv7 model: The YOLO[11] network model, as the most typical representative in one-stage object detection algorithms, mainly conducts object recognition and location based on deep neural networks. Due to its fast running speed, it can be applied to real-time systems. YOLOv7 (You Only Look Once v7) inherits the characteristics of fast computing and accurate recognition of the YOLO series, and optimizes the corresponding performance. The model is composed as follows:

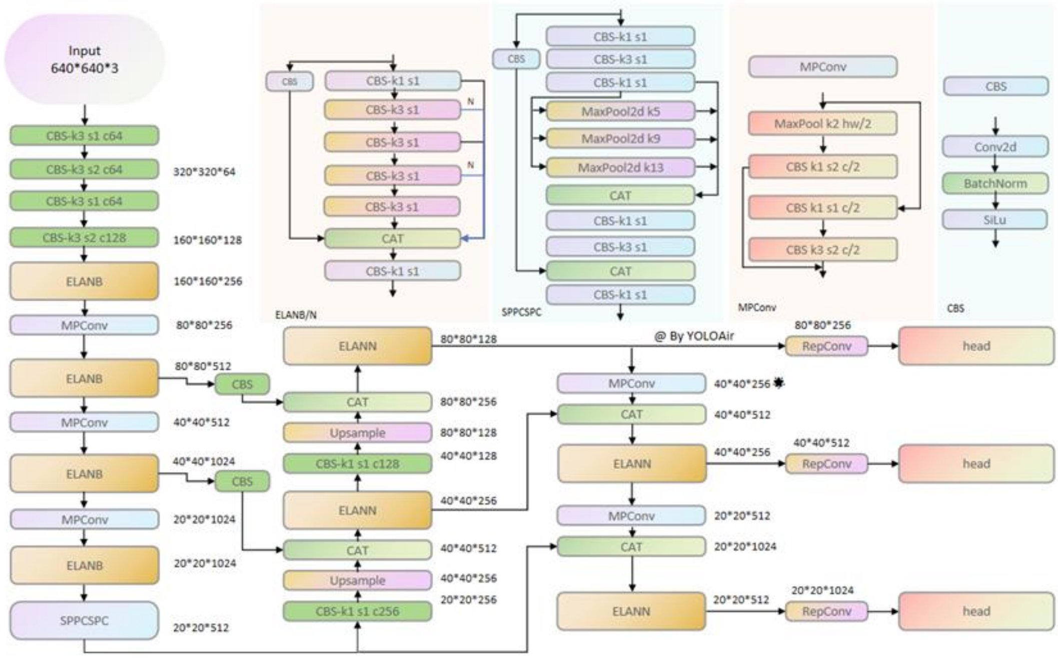

Fig.1 YOLOv7 model

Lightweight GhostNetV2 module: The core of GhostNetV2 is the GhostNetV2[12] Bottleneck module, whose schematic diagram is shown in Figure 2. Through the DFC attention module and the first Ghost module, its extended features are enhanced in parallel. The enhanced features are input into the second Ghost module to generate output features. Thereby enhancing the representation ability of GhostNetV2. The research found that after improvement, higher experimental accuracy could be achieved, and better performance could be obtained under the premise of reducing the number of parameters.

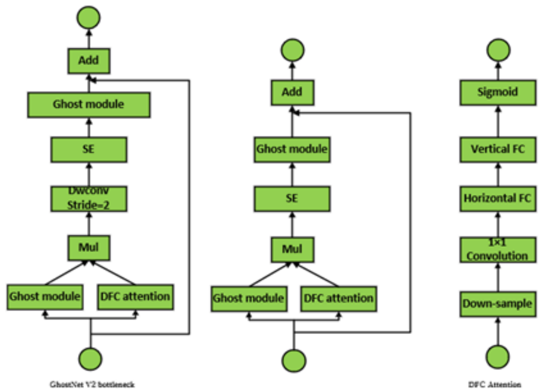

Fig.2 GhostNetV2 Bottleneck module

Therefore, introducing GhostNetV2 into the YOLOv7 network to replace conventional convolution significantly reduces the number of parameters and computational load without sacrificing model accuracy, thereby enhancing the detection speed of the network.
The network structure parameters of GhostNetV2 are shown in the following table.

Table 1: Network structure parameters of GhostNetV2

Input data	Convolutional block	Output dimension	DFC	Compression ratio S
640×640×3	Conv3×3	16		2
320×320×16	Ghost Bottleneck v2	16		1
320×320×16	Ghost Bottleneck v2	24	1	2

160×160×24	Ghost Bottleneck v2	24	1	1
160×160×24	Ghost Bottleneck v2	40	1	2
80×80×40	Ghost Bottleneck v2	40	1	1
80×80×40	Ghost Bottleneck v2	80	1	2
40×40×80	Ghost Bottleneck v2	80	1	1
40×40×80	Ghost Bottleneck v2	80	1	1
40×40×80	Ghost Bottleneck v2	80	1	1
40×40×80	Ghost Bottleneck v2	112	1	1
40×40×112	Ghost Bottleneck v2	112	1	1
40×40×112	Ghost Bottleneck v2	160	1	2
20×20×160	Ghost Bottleneck v2	160	1	1
20×20×160	Ghost Bottleneck v2	160	1	1
20×20×160	Ghost Bottleneck v2	160	1	1
20×20×160	Ghost Bottleneck v2	160	1	1
20*20*160	Ghost Bottleneck v2	960	1	1

BiFPNFeature Fusion module:

The full name of BiFPN[13] is Bidirectional Feature Pyramid Network, a weighted bidirectional (top-down + bottom-up) feature pyramid network. The main idea is to aggregate features of different scales by using top-down and bottom-up paths. This enables features of all scales to contain rich semantic and detailed information. At the same time, a fast normalization fusion technique was used, that is, a weight was added to each input feature, allowing the network to learn the importance of each feature, and all the conventional convolution was replaced with a lighter depth-separable convolution.

Weighted feature fusion uses Fast normalized fusion.It directly normalizes by dividing the weights by the sum of the weights, and normalizes the weights to between [0,1] at the same time, which improves the calculation speed. The fusion method is shown in Formula (1) :

$$O=\sum_i \frac{w_i \cdot I_i}{\varepsilon+\sum_j w_j} \tag{1}$$

In the formula, w represents the weight parameter learned by the network. The Relu function is used to calculate the weights trained by the network so that w is greater than or equal to 0. "I represents the feature of the input;" ε=0.0001 is a small value to avoid numerical instability. The improved network will extract feature maps of different scales as the input of the feature fusion layer, and then perform bidirectional cross-scale connection and weighted feature fusion. Let Pi be any output layer, and the characteristics after fusion are:

$$P_i^{td}=Conv\left(\frac{w_j \cdot P_i^{in}+w_{j+1} \cdot Resize(P_{i+1}^{in})}{w_j+w_{j+1}+\varepsilon}\right) \tag{2}$$

$$P_i^{out}=Conv\left(\frac{w_j' \cdot P_i^{in}+w_{j+1}' \cdot P_i^{td}+w_{j+2}' \cdot Resize(P_{i-1}^{out})}{w_j'+w_{j+1}'+w_{j+2}'+\varepsilon}\right) \tag{3}$$

In the formula, Resize usually represents the upsampling or downsampling operation; w indicates that the network has learned weight parameters, which can be used to distinguish the importance of different connections in feature fusion.

Loss function:

In object detection algorithms, the loss function is often used for parameter optimization of the model. Among them, the target bounding box loss function mainly calculates the distance deviation between the real box and the predicted box. The calculated loss value is then corrected through backpropagation to adjust the model weight parameters, making the predicted box continuously approach the real box. Therefore, selecting an appropriate bounding box loss function is very important in detection tasks. In Yolov7, CIoU is adopted as the loss function[14]. During the calculation of the loss value, the aspect ratio of the predicted box and the real box is taken into account, enabling the model to capture the shape information of the target more accurately. The loss function formulas are shown in equations (4), (5), (6), and (7):

$$CIOU=IOU-\left(\frac{\rho^2(b,b^{gt})}{c^2}\right)+av \quad (4)$$

$$L_{CIOU}=1-CIOU \quad (5)$$

$$v=\frac{4}{\pi^2}(\arctan\frac{w^{gt}}{h^{gt}}-\arctan\frac{w}{h})^2 \quad (6)$$

$$\alpha=\frac{v}{(1-IOU)+V} \quad (7)$$

Among them, b represents the coordinates of the center point of the prediction box, bgt represents the coordinates of the center point of the real box, ρ2 is the Euclidean distance between the center point of the prediction box and the real box, and c is the minimum diagonal length of the outer box of the prediction box and the real box. c and h are the width and height of the box respectively; v represents shape loss, which is used to measure the proportional consistency between the width and height of the predicted box and the actual box.

The SIOU[15] loss function takes into account the distance between the prediction box and the target box, the overlap rate, and the influence of vector angles during the training process. It not only ensures a fast convergence speed but also effectively avoids the divergence phenomenon during the training process.

To more intuitively demonstrate the specific roles of each parameter in the SIoU loss function, Figure 3-10 shows the schematic diagrams of the corresponding parameters in the SIoU loss. It can be observed from the figure that each parameter works together to achieve the best match between the predicted box and the real box.

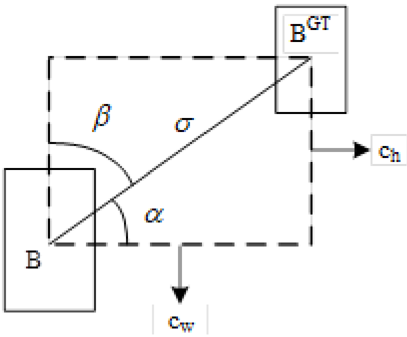

Fig.3 Schematic diagrams of each parameter in the SIoU loss function

The SIoU loss first brings the prediction to the X-axis or Y-axis (whichever is closest), and then continues to approach along the relevant axes.If $\alpha \leq \pi/4$, he convergence process will first minimize α, otherwise,β will be minimized, $\beta = \pi/2 - \alpha$.The formula for angular loss is as follows:

$$\Lambda = 1-2*\sin^2(\arcsin(\frac{c_h}{\sigma})-\frac{\pi}{4}) = \cos(2*(\arcsin(\frac{c_h}{\sigma})-\frac{\pi}{4}) \quad (8)$$

IV. Analysis Of Experimental Results

Ablation experiment:

This study designed GhostNetV2, BIFPN and SIOU modules that are more suitable for substation defect detection tasks. The influence of different modules on the model detection effect was systematically studied through ablation experiments. It was found that when the number of parameters was reduced by half, the average precision was improved to 0.957.

Table 2: Ablation experiment of substation anomaly detection algorithm

Model	GhostNetV2	BIFPN	SIOU	P	R	mAP50	Params	FLOPs	FPS	Weights
1	×	×	×	90.9%	86.9%	93.4%	37.2M	105.2G	227	71.4MB
2	√	×	×	91.3%	87.9%	94.0%	26.2M	42G	278	50.5MB
3	×	√	×	92.9%	90.9%	94.4%	36.2M	103.6G	227	69.5MB
4	√	√	×	92.7%	91.3%	94.6%	25.2M	40.5G	270	48.7MB
5	√	√	√	93.7%	92.1%	95.7%	25.2M	40.5G	270	48.8MB
6	×	×%	√	90.9%	88.8%	94.2%	37.2M	105.2G	227	71.4MB

7	×	√	√	91.6%	93%	95.9%	37.2M	105.2G	227	71.4MB
8	√	×	√	92.5%	90.8%	94.7%	26.2M	42G	270	50.5MB

The experimental results show that the backbone network improved by the GhostNetV2 lightweight module has a 11MB reduction in model parameters, a 150% decrease in FLOPs, and a 22% increase in FPS while maintaining the average precision (mAP) basically unchanged. This proves the adaptability of GhostNetV2 in the lightweight design of models. At the same time, it can also maintain the accuracy level of the model; After adopting the feature fusion BIFPN module, the average precision (mAP) was increased by 1% with the number of parameters remaining basically unchanged, which proved the advantages of the BIFPN module in feature extraction and detection accuracy. After replacing the SIOU module with the loss function optimization, with the number of model parameters and FPS remaining unchanged, the recall rate R increased by 1.9% and the average precision (mAP) improved by 0.8%, indicating that the SIOU module captures the shape information of the target more accurately, but the number of model parameters cannot be changed. After the combination of the three modules, the accuracy rate P increased by 2.8%, the recall rate R increased by 5.2%, the average precision (mAP) increased by 2.3%, the number of model parameters decreased by 12MB, the FLOPs decreased by 64.7G, and the FPS increased by 19%. This significantly improved the detection accuracy of the model, while greatly reducing the number of model parameters and enhancing the computational efficiency. In addition, the ablation experiments of GhostNetV2+BIFPN[16], GhostNetV2+SIOU[17], and BIFPN+SIOU[18] verified the efficiency of module collaboration. The improved YOLOv7 model outperformed other comparison models in terms of detection speed and accuracy.

According to the analysis of the ablation experiment, introducing GhostNetV2 into the YOLOv7 network to replace the conventional convolution can significantly reduce the number of model parameters and improve the detection speed without sacrificing model accuracy. By constructing a bidirectional cross-scale path aggregation network structure (BiFPN) in the feature fusion network, reusing and extracting the key feature layers, and using deep networks for feature fusion of different scales, the accuracy of model detection can be improved. The SIoU loss function substitution, by optimizing the regression of the prediction box, realizes the dynamic adjustment of the regression loss of the prediction box, further improving the detection accuracy of the network.

Comparative test：

The comparative experiments involve different types of object detection algorithms, including the classic algorithm Faster R-CNN[19] in Two-Stage detectors, the classic algorithm SSD[20] in One-Stage detectors, DETR based on Transformer, and various YOLO series algorithms. Including models such as YOLOv3, YOLOv5s, GOLD YOLO-s, and YOLOv7. The model was trained and tested under the condition that the dataset and hyperparameters remained unchanged, verifying the advantages of the improved algorithm. The results are shown in Table 3.

Table 3: Comparative experiments of different algorithms on the substation anomaly detection dataset

Model	mAP50	Params	FLOPs	FPS	Weights
Faster R-CNN	90.10%	42M	180G	29	315MB
SSD	79.00%	24.1M	273G	108	190MB
YOLOv3	82.00%	61.57M	155.4G	127	470MB
YOLOv5s	85.20%	7.05M	16G	333	13.8MB
YOLOX-s	88.90%	8.94M	26.78G	180	68.5MB
DETR	77.60%	41.28M	86G	28	474MB
YOLOv8m	91.70%	25.8M	78.7G	189	49.6MB
YOLOv7	93.40%	37.29M	105.4G	227	71.4MB
PP-YOLO-s	86.20%	177.26M	106.7G	101	339MB
GOLD YOLO-s	92.50%	21.51M	46.04G	269	44.6MB
Our	**95.70%**	**25.2M**	**40.5G**	**270**	**48.8MB**

From the comparative experiments, it is known that YOLOv5s has the fastest detection speed, but it sacrifices detection accuracy, which is only 85.2%. GOLD YOLO-s has a detection speed basically the same as the algorithm in this chapter, but its detection accuracy is 3.2% lower. In conclusion, the model in this chapter can achieve the best experimental accuracy, while ensuring a relatively small number of parameters and a high detection speed, which can meet the requirements of accuracy and real-time performance in actual inspection.

Figure 4 shows the distribution of accuracy and detection speed of different algorithms in Table 3 under the infrared image defect detection dataset of substation equipment. Figure 5 shows the mAP value curve of the improved YOLOv7 algorithm in this chapter.

The six substation equipment categories, namely transformer bushings, defective bushings, circuit breakers, defective circuit breakers, isolation knife switches, and defective knife switches, were classified in the same scenario and compared with the above algorithms respectively to verify the advantages of the improved YOLOv7 algorithm. The recognition results are shown in Figure 6.

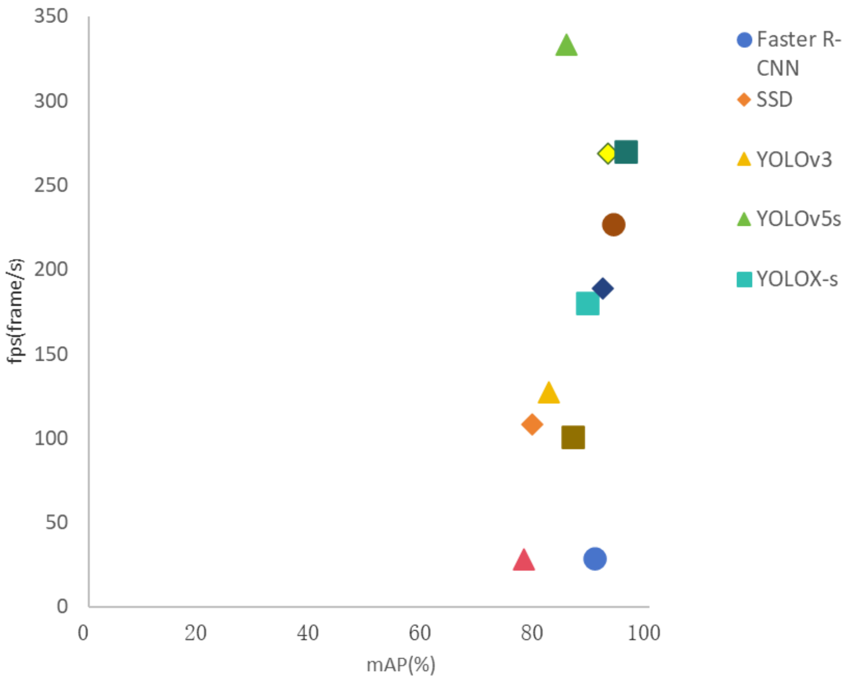

Fig.4 Distribution map of detection accuracy and detection speed of different models

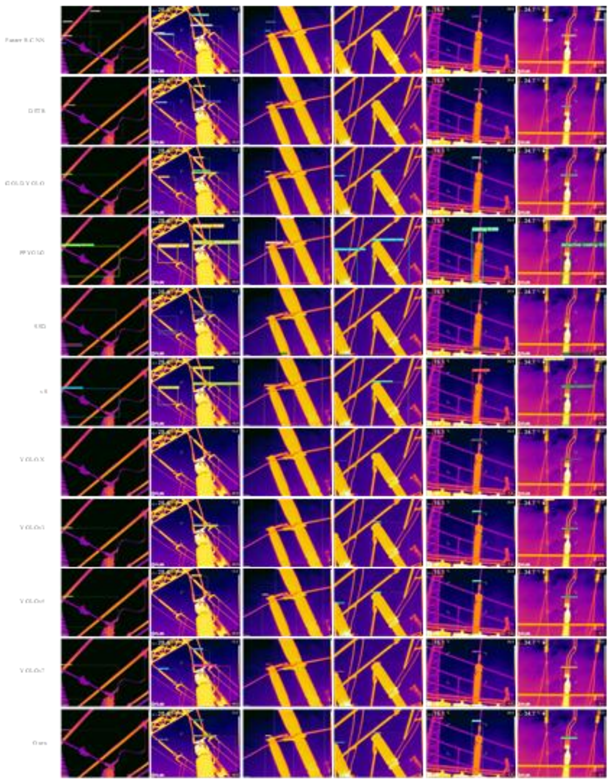

Fig.5 Comparison of infrared image defect detection results of substation equipment under different models

V. Conclusion

To meet the requirements of rapid defect detection in infrared images of power transformation equipment, an improved YOLOv7 model was designed. By introducing the GhostNetV2 module to replace the conventional convolution in the YOLOv7 network, the number of model parameters has been significantly reduced. Design a bidirectional cross-scale path aggregation network structure (BiFPN)[21], reuse and extract the key feature layers, and improve the feature extraction ability of the network; The SIoU[22] loss function is adopted to dynamically adjust the regression loss of the prediction box, thereby enhancing the convergence speed and detection accuracy of the network. After a series of ablation and comparative experiments, the results show that the defect detection model for infrared images of substations designed in this chapter has a 2.3% improvement in detection accuracy compared to YOLOv7, while the model size is reduced by 32%. When the model size is basically the same as that of YOLOv8m, the detection accuracy is increased by 4% and the detection speed by 43%. It can be concluded from this that the improved YOLOv7 model has achieved relatively ideal improvements in both defect detection accuracy and detection speed.

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