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Insulator and Its Defect Detection Based on Lightweight YOLOv5s

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Abstract. In order to achieve precise and real-time detection of insulators and their defects by drones, a lightweight YOLOv5s based insulator and its defect detection model YOLOv5s-SGCS-GB-4PH was designed. Firstly, the lightweight network Shufflenetv2-Ghostconv-Conv-SimSPPF (SGCS) was used as the backbone network of YOLOv5s, effectively reducing the number of parameters and complexity of the model; Secondly, introducing GSConv into the neck network to improve model efficiency; Then, a bidirectional feature pyramid network and an additional small target detection head are used to improve the model's ability to perceive insulators and their defects; Finally, SioU-VF loss function is selected to obtain better target location and improve model accuracy. The experiment shows that the YOLOv5s-SGCS-GB-4PH model reduces the parameter and computational complexity by 34.3% and 48.1% respectively on self-made insulator data, and improves the detection accuracy by 3.6%, achieving a balance between lightweight and detection accuracy. It is more suitable for deployment on unmanned aerial vehicles for real-time detection of insulators and their defects.

Keywords. insulator and its defect; YOLOv5s; lightweight; Shufflenetv2

1. Introduction

As an important part of the transmission line, the insulator has the function of mechanical support and electrical insulation for the transmission line[1]. Due to long-term exposure to the complex natural environment, the insulator will appear string, defects, flashover and other defects. In order to reduce various transmission line failures caused by insulator defects, insulators must be inspected frequently.

In recent years, insulator and defect detection methods based on deep learning have been continuously optimized. K.He et al.[2] introduced the fully convolutional neural network FCN based on Faster RCNN to generate Mask branches, and proposed the Mask RCNN algorithm. Zhang et al.[3] proposed a Faster R-CNN glass insulator detection algorithm based on morphological processing to avoid the interference of complex background on insulator defect detection. Qiu et al.[4] used MobileNet to improve the structure of YOLOv4 model, which improved the problem of too many parameters and slow detection of YOLOv4. Han et al.[5] integrated ECA-Net and Soft-nms into YOLOv5, reducing the probability of deleting overlapping targets by mistake. The above scheme effectively improves the detection accuracy, but there is still room for improvement in the lightweight design of the number of model parameters and complexity.

In order to realize the accurate and real-time detection of insulators and their defects

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by UAV, a lightweight YOLOv5s based insulator and its defect detection model, YOLOV5S-GCS-GB-4PH, is designed in this paper. It solves the problems encountered by UAV in insulator and defect detection process, such as difficult to detect small defective targets, complex target overlap and background, and difficult to deploy mobile devices with large model volume, and realizes the balance between lightweight and detection accuracy.

2. YOLOv5S-SGMS-GB-4pH network

2.1 Network Model Improvement

The YOLOv5s-SGCS-GB-4PH network proposed in this paper consists of three parts: Shufflenetv2-Ghostconv-Conv-SimSPPF feature extraction module, multi-scale feature fusion module of GSConv and BiFPN, and four prediction head module. The improved network model structure is shown in Figure 1.

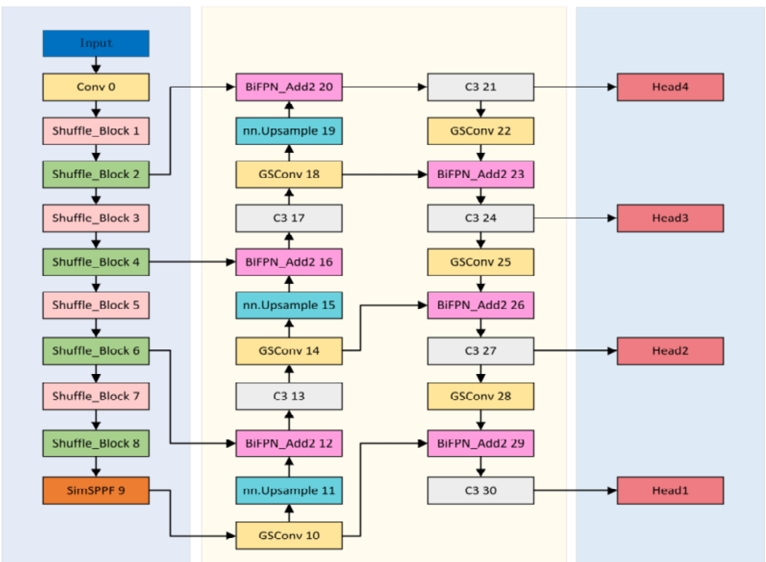


Figure 1. Improved network structure

Shufflenetv2-ghostconv-conv-simsppf feature extraction module is based on Shufflenetv2 network, replacing DW convolution with Ghost convolution, CBRM module with Conv module, and introducing more efficient SimSPPF module. The multi-scale feature fusion module of GSConv and BiFPN replaces standard convolution with phantom convolution and PA-FPN with BiFPN structure. Four prediction head module adds a small target detection head.

2.2 Shufflenetv2-Ghostconv-Conv-Simsppf feature extraction module

C3Net, the backbone of YOLOv5s, contains a large number of convolution and bottleneck structures, generating huge floating point operations, convolutional addition and multiplication. Shufflenetv2 follows four lightweight network design criteria, namely, using "balanced" convolution, eliminating group convolution, reducing network fragmentation, and reducing element operations[6].

The DW convolution operation is carried out independently for each channel in the input layer, and the feature information of different channels in the same spatial position cannot be effectively utilized. In this paper, Ghost volume integration is adopted in two steps. First, the feature graph with smaller channel is generated through traditional convolution. Then, on the basis of the obtained feature graph, lightweight linear transformation is used to further reduce the calculation amount and generate a new feature graph. The feature extraction performance is guaranteed and the number of parameters is reduced.

The first layer of the original Shufflenetv2 network is a CBRM structure, and the maximum pooling operation contained in it will cause the loss of feature information. The standard convolution replacement can ensure the integrity of the feature information of the network with less parameter growth. By introducing SimSPPF to fuse the local and global features of insulators and their defects, the semantic information of feature graphs can be enriched. In addition, compared with SPPF network, SimSPPF can not only effectively solve the problem of image distortion and repeated extraction of related features, but also significantly improve the speed of model detection by introducing ConvBNReLU module[7].

2.3 GSConv-BIFPN Feature fusion module and 4PH

GSConv is used in Neck to process concatenated feature maps to ensure the integrity of semantic information without generating redundant and repetitive information[8].

BIFPN simplifies the PA-FPN structure and effectively prevents the loss of small targets by fusing large-scale feature mappings that contain more information about small targets[9].

In this paper, a small target prediction head is added after the 160 × 160 feature map, which can effectively improve the insulator defect sensing ability of the model.

2.4 Improvement of Loss Function

The CioU-BCE Loss adopted by YOLOv5s could not reflect the real difference between length and width respectively and their confidence degrees, and could not distinguish positive and negative samples well[10]. Therefore, this paper adopts SioU-VF Loss to calculate the loss, which consists of four loss functions, including Angle loss, distance loss, shape loss and intersection ratio loss[11]. After experimental verification, the adoption of SioU-VF Loss in this paper can effectively balance the vector Angle between positive and negative samples and expected regression, and enhance the convergence rate of loss and the accuracy of positioning.

3. Production of Data Sets

3.1 Data Enhancement

The self-made dataset includes ceramic insulators, glass insulators, and composite insulators, and divides them into four categories: insulator, defect, string drop, and flashover. In order to restore the shooting effect of UAV under different weather conditions, the data set was expanded to 5327 images by using different Angle rotation, scaling, mirroring, cropping, brightness change, Gauss and salt and pepper noise.

3.2 Image Annotation

LabelImage was used to annotate the data set, divide the data set into training set, verification set and test set according to 7:2:1, and then convert the xml format data set into txt format to meet the data format requirements of YOLOv5s model.

4. Experimental Results and Analysis

4.1 Comparative Experiments of Different YOLOv5s Backbone

In this paper, the advantages of the ShuffleNetV2-Ghostconv-Conv-SimSPPF lightweight backbone network proposed in this paper are verified by the comparative experiments of ten different backbone networks of YOLOv5s, and the results are shown in Table 1.

Table 1. Comparative experiments of different YOLOv5s backbone

Backbone	mAP	FPS	Params/M	GFLOPs
C3Net	92.2	73	7.0	15.8
EfficientNetV2	84.5	86	5.4	5.6
FasterNet	84.7	80	6.7	7.8
GhostNetV2	88.2	48	3.7	6.5
MobileNetV3	88.6	82	5.0	11.3
ShuffleNetV2	88.2	85	3.8	7.0
ShuffleNetV2-Ghostconv	89.3	81	4.0	7.4
ShuffleNetV2-Ghostconv-Stem	90.2	42	3.8	36.2
ShuffleNetV2-Ghostconv-Conv	90.1	78	4.1	7.5
ShuffleNetV2-Ghostconv-Conv-SimSPPF	90.7	75	4.2	7.8

It can be seen from the results of Table 1 that ShuffleNetV2 has the best comprehensive performance among the five lightweight networks. To compensate for the loss of precision caused by lightweight, Ghostconv is used to replace deep convolution and form SG network. Using Stem and Conv to replace CBRM to form SGS and SGC networks respectively, Stem modules bring irreparable losses to detection speed and computation, while SGC network can effectively make up for the loss of accuracy, with little loss of detection speed. Finally, SimSPPF is introduced to form the SGCS network, and the detection accuracy of the lightweight network is increased from 88.2% to 90.7%.

4.2 Ablation Experiment of YOLOv5s-SGCS-GB-4PH Network Model

In order to verify the comprehensive performance of the YOLOV5S-SGCS-GB-4PH network model and the effectiveness of each module, ablation experiments were conducted on the basis of the YOLOv5s-SGCS model with single improvement and fusion of improved methods, and the results were shown in Table 2.

Table 2. Ablation experiment of YOLOv5s-SGCS-GB-4PH network model

Group	GSConv	BiFPN	4PH	SIoU-VF	mAP	FPS	Params/M	GFLOPs
1					90.7	75	4.2	7.8
2	√				92.3	83	3.7	6.9
3	√	√			93.5	80	4.0	7.2
4	√	√	√		95.2	76	4.6	8.2
5	√	√	√	√	95.8	76	4.6	8.2

This experiment verified the good performance of the YOLOV5S-SGCS-GB-4PH model. Although a few parameters and complexity were added to the YOLOv5s-SGCS model, the detection speed of the model was improved, and the accuracy was increased by 5.1%, reaching 95.8%.

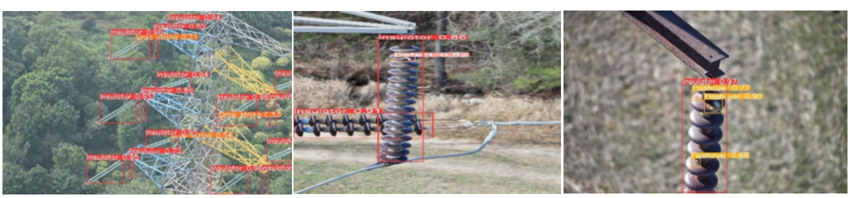
4.3 Verify the Performance of the YOLOV5S-SGMS-GB-4PH Network Model

In order to verify the detection effect of YOLOv5s-SGCS-GB-4PH network model, comparative experiments were conducted on the Faster RCNN, SSD and YOLO series models on self-made insulators and their defect data sets.

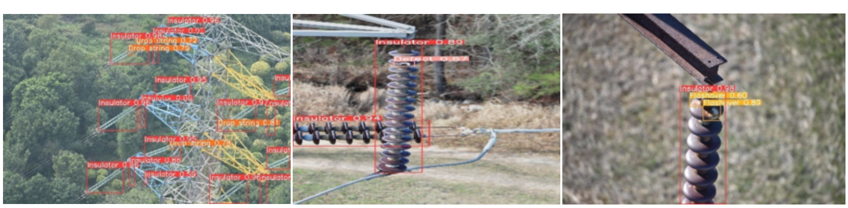
Table 3. Comparative experimental results of different detection models

Model	mAP	FPS	Params/M	GFLOPs
Faster RCNN	93.4	12	72.2	26.6
SSD	81.2	28	25.5	33.4
YOLOv3	92.6	32	61.5	193.8
YOLOv4	91.5	37	52.5	119.5
YOLOv5s	92.2	73	7.0	15.8
YOLOv7-Tiny	89.4	54	6.0	13.0
YOLOv5s-SGCS-GB-4PH	95.8	76	4.6	8.2

As can be seen from the comparative experimental results in Table 3, compared with YOLOv5s, the Yolov5S-SGMS-GB-4PH model, while the detection speed is slightly improved, the number of parameters is compressed by 34.3%, the calculation amount is decreased by 48.1%, and the detection accuracy is increased by 3.6%, reaching 95.8%.



(a) Test results of YOLOv5s model



(b) Test results of YOLOV5S-SGMS-GB-4PH model

Figure 2. Comparison of test results between YOLOv5s and YOLOV5S-SGMS-GB-4PH

In figure 2 (a), the highest detection accuracy of string drop defects is only 71%, and the detection accuracy of defect defect is 82%, and there are problems such as string miss detection, flashover error detection, and poor anchor frame positioning. In figure 2 (b), the detection accuracy of string drop defects reached 81%, the accuracy of defects was 87%, and the detection accuracy of insulators was 98%. The missed string drop defects could not only be detected, the misdetection of flashover defects could be eliminated, but also the anchor frame range of the insulators and their defects could be better fitted to the detection target. It can be seen that the YOLOv5s-SGCS-GB-4PH model has a good detection effect on insulators and their three defects, and can be deployed on UAVs for real-time detection of insulators and their defects.

5. Conclusion

The lightweight YOLOv5s-SGCS-GB-4PH model proposed in this paper for insulator and defect detection solves the problems encountered by UAVS in insulator and defect detection, such as difficult detection of small defect targets, complex target overlap and background, large model size and difficult deployment of mobile devices, etc. A large number of experiments on self-made data sets show that, The YOLOv5s-SGCS-GB-4PH model compressed the parameter number and calculation amount of 34.3% and 48.1%, while improving the detection accuracy of 3.6%, speeding up the detection speed, and achieving the balance of lightweight and detection accuracy, which is conducive to the deployment of mobile devices such as drones and the real-time detection of insulator and its defects.

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