Application of Yolov5 Algorithm in Identification of Transmission Line Insulators

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Abstract. As an important infrastructure, the power system assumes a position that cannot be ignored in the national economy. The insulator in the transmission line is one of the main components of the power system. A complete and defect-free insulator is a prerequisite to ensure a good insulation between the current-carrying conductor and the ground. At present, it has become a mainstream practice to identify insulators through drones. However, due to the small number and single types of insulator data currently disclosed, the network does not have a large number of samples to learn more characteristics of insulators, which hinders the improvement of the accuracy of the network model to a certain extent. In this article, based on the existing 848 transmission line insulator data set, we train the yolov5 algorithm to generate a network with a recognition rate. The experimental results show that the mAP of the trained model is 11.41% higher than that of J-Method and 37.25% higher than the average of the other four methods mentioned by J-Method.

Keywords: Transmission line · Insulator · Yolov5 · Algorithm · Data enhancement

1 Introduction

As an important infrastructure, the power system assumes a position that cannot be ignored in the national economy [1]. The insulator in the transmission line is one of the main components of the power system. A complete and defect-free insulator is a prerequisite to ensure a good insulation between the current-carrying conductor and the ground. At present, it has become a mainstream practice to identify insulators through drones. Traditional manual identification of insulators in high-voltage transmission lines is extremely difficult, which is mainly manifested in the high identification cost and low identification efficiency and the inability to identify insulators in complex geographic environments.

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In recent years, A series of intelligent autonomous identification algorithms have been produced, which can identify the defects of insulator equipment in time with the rapid development and continuous application of computer vision and image recognition technology. Liu et al. propose an improved algorithm based on Faster-RCNN for the presence of complex foreign bodies in the substation environment, which strengthens the detection of small targets [2]. However, there are certain sample scene differences in the identification of insulator defects, and the identification efficiency is very low. Jiang et al. combine the Faster R-CNN algorithm and the Soft-NMS algorithm to solve the identification of insulator defects in the interference environment, but only limit to a small increase in the average identification efficiency [3]. Based on the idea of segmentation network, Gao et al. propose a Mask R-CNN algorithm to improve the performance of the model [4], but this method is based on infrared image recognition. Aiming at the complexity of the transmission line image, Hou et al. integrate the AlexNet, VGG16 and Faster R-CNN network structures, but the redundancy of the network structure reduces the recognition efficiency [5].

In this paper, we use the yolov5 algorithm for sample training and insulator image defect recognition, which improves the accuracy and mAP value of algorithm recognition, and effectively solves the problem of inaccurate recognition of insulator defects in actual line inspection scenarios.

2 Insulator Data Enhancement

2.1 Introduction to U-Net Network

U-Net is proposed in 2015, which is an Encoder-Decoder structure and used to solve the problem of medical image segmentation. The U-Net network structure is shown in Fig. 1. On the left is the decoding process, which consists of convolution operation and pooling layer downsampling. On the right is the encoding process, which is restored to the original resolution after up-sampling. A skip-connection is added during the decoding and encoding process, and the entire network has a U-shaped symmetrical structure [6]. U-Net uses data enhancement methods such as translation, rotation, and elastic deformation during training to make up for the lack of data [7]. Since the number of transmission line insulators is too small to be used to train large-scale instance segmentation networks like Mask-RCNN, U-Net network is adopted [8]. Firstly, we label the insulator position on the image that taken by the transmission line for creating insulator Dataset. Secondly, we train the Dataset with U-Net network and generate a model.Thirdly, we use the model to predict other unlabeled insulator Dataset and segment the insulator masks. Finally, the segmenting insulator masks are overlaid on the image of ordinary transmission line, which to generate a new insulator Dataset for increasing the yolov5 training samples.

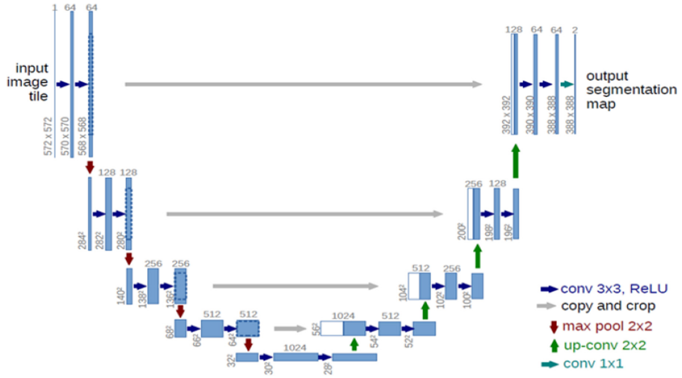

Fig. 1. U-Net network structure that comes from https://blog.csdn.net/fang_chuan/article/details/94965995

2.2 Data Enhancement

At present, the transmission line Insulator Dataset(In-D) is one of the frequently used datasets, with a total of 848 [9]. The data consists of two parts: normal insulators(Nor-Ins) and defective insulators(Def-Ins). Nor-Ins are 600 images of normal insulators captured by drones. Def-Ins are 248 insulator images, which are all generated through the following five steps of data enhancement:

Step 1: Use the TVSeg tool to segment the insulator from a small part of the original image, and the result of the segmentation is the mask image of the insulator;

Step 2: Use Affine Transform to randomly rotate, mirror, blur, add noise, Cutout, etc. to the original image and its insulator mask image to achieve data enhancement;

Step 3: Use the enhanced insulator mask image (including the coordinate position) to train the U-Net network;

Step 4: Use the trained U-Net network to segment the insulator mask image and the original background image (Background) of the original image;

Step 5: Generate different image data sets containing insulators.

After data preprocessing, 648 training sets and 200 test sets are finally generated. The test sets used in this paper are all images normally containing insulators taken by drones, the purpose is to ensure that the model is not over-fitting and can reflect the true accuracy rate.

3 Introduction to Yolov5 Algorithm

YOLOv5 is a single-stage target detection algorithm [10]. The algorithm adds some new improvements on the basis of YOLOv4, which greatly improves its speed and accuracy [11]. The architecture diagram of YOLOv5 is shown in Fig. 2 and the main improvement ideas are as follows:

(1) Input terminal: In the model training stage, some improvement ideas are proposed, mainly including Mosaic data enhancement, adaptive anchor frame calculation, and adaptive image scaling;

(2) Benchmark network: integrate some new ideas in other detection algorithms, mainly including Focus structure and CSP structure;
(3) Neck network: The target detection network often inserts some layers between BackBone and the final Head output layer, and Yolov5 just adds the FPN + PAN structure;
(4) Head output layer: The anchor frame mechanism of the output layer is the same as YOLOv4. The main improvements are the loss function GIOU_Loss during training and the DIOU_nms filtered by the prediction frame.

The YOLOv5 algorithm has 4 versions, and yolov5 is divided into four models according to size: yolov5s, yolov5m, yolov5l, and yolov5x [12].

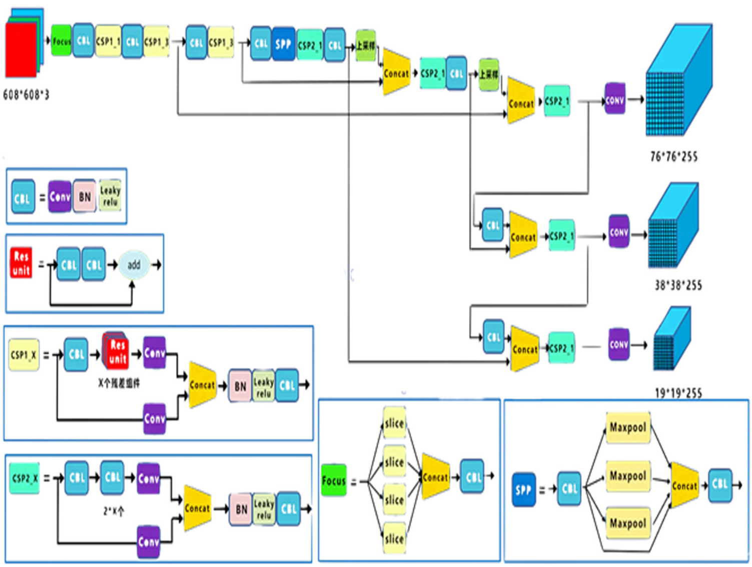

Fig. 2. YOLOv5 architecture diagram that comes from https://www.jianshu.com/p/4c348d78143e

4 Experiment

4.1 Experiment Preparation

The data set used in this experiment is In-D, the training data and the test data are 648 and 200, respectively, accounting for 76.42% and 23.58% of the total data. In the experiment, it is divided into 21 batches, and each batch size is 32 sheets. The size of each image is 640x640, with a total of 50 epochs before and after iteration. The running configuration environment of the experiment is shown in Table 1. The operating system is Ubuntu 18.04, the programming language is Python 3.6, and the training framework is Pytorch 1.7.1.

Table 1. The running configuration environment of the experiment

Experimental environment	Configuration
Operating system	Ubuntu 18.04
CPU	Intel(R) Xeon(R) Gold 6230 CPU @ 2.10 GHz
RAM /GB	188
Programming language	Python 3.6
Deep learning framework	Pytorch 1.7.1

The key metrics used in the experiment are precision rate (P), recall rate (TPR) and mAP value. The specific formula is as follows [13]:

$$\mathrm{P(Precision)} = \mathrm{TP} / (\mathrm{TP} + \mathrm{FP}) \tag{1}$$

$$\mathrm{TPR} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}) \tag{2}$$

$$\mathrm{mAP} = \frac{\sum_{i=1}^{K} AP_i}{K} \tag{3}$$

Where:

$$p_{\mathrm{int}\ erp}(r) = \max_{r' \geq r} P(r')$$

$$AP = \sum_{i=1}^{\mathrm{n\ -\ 1}} (r_{i+1} - r_i) p_{\mathrm{int}\ erp}(r_{i+1})$$

$$r = TP/(TP + FN)$$

Where True Positive (TP) means that the true result is P and the predicted result is P, False Positive(FP) means that the true result is N and the predicted result is P, True Negative (TN) means that the true result is P and the predicted result is N, False Negative (FN) means that the true result is N and the predicted result is N, Recall(r) refers to the proportion of positive examples (TP + FN) correctly identified by the model to all positive examples in the Dataset, K is the number of categories., AP represent how good or bad the trained model is in the current category.

4.2 Experimental Result

The YOLOv5 algorithm was used in the experiment, and four models of YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x were tried respectively. The network structure of these four models is the same, but the depth of the model and the number of convolution kernels are different, which results in different model sizes.

As shown in Fig. 3, the size of the four models YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x are 14.4MB, 42.5MB, 93.7MB and 175.1MB, respectively. It can be clearly seen that the depth of YOLOv5x is 607 layers, and the capacity of its model is also the largest of the four models, 175.1MB, which is 2.15 times higher than the average size of the four models.

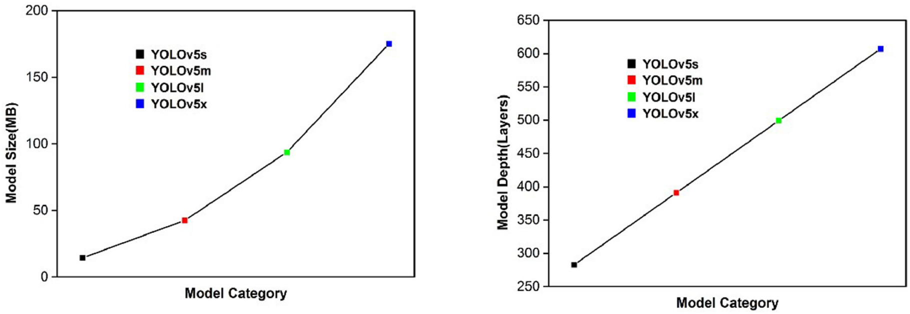

Fig. 3. The size and depth of the four models of YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x

According to the three indicators previously set to measure the quality of the model, we test the four types of networks. As shown in Fig. 4a, YOLOv5l has the highest P index among the four models, 0.9263. YOLOv5l ranks second in the R index of the four models, which is only 0.03 lower than the highest R index (YOLOv5x), as shown in Fig. 4b. This data shows that YOLOv5l and YOLOv5x have very similar performance in terms of R index.

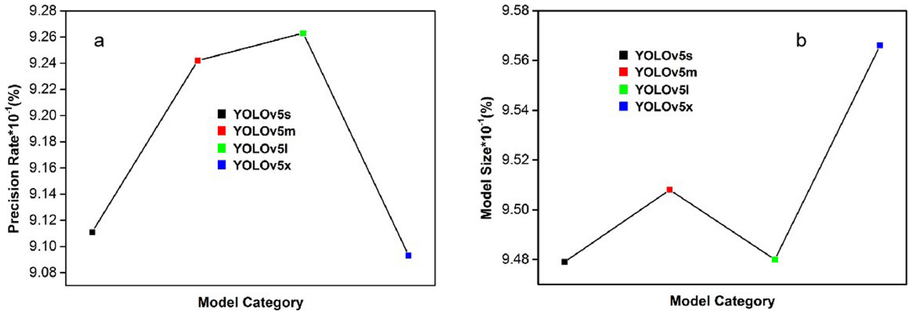

Fig. 4. a) The P and b) R index of the four models of YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x.

Based on the index P and the index R, and according to the calculation rules of mAP, it is concluded that the mAP value of YOLOv5l is the highest (0.9727). This data shows that the overall performance of this model is the best. It is worth noting that although YOLOv5x is not the best of the four models, its mAP value is very close to that of YOLOv5l, and the difference between the two is only 0.03, as shown in Fig. 5a. Compared with the latest report of J-Method [14], YOLOv5l is 11.41% higher than its improved method and 37.25% higher than the average of the other four methods mentioned (Fig. 5b). That can be seen from the above data that YOLOv5l does have a great improvement in performance.

This experiment is only based on the actual business needs of the power system. The key considerations are the P index, R index and mAP value. Therefore, the calculation cost is not considered here. For operations that require particularly stringent accuracy in the power system business, it is recommended to use the YOLOv5l model. For businesses with general accuracy requirements and limited computing resources, it is recommended to use YOLOv5s and YOLOv5m with smaller model size.

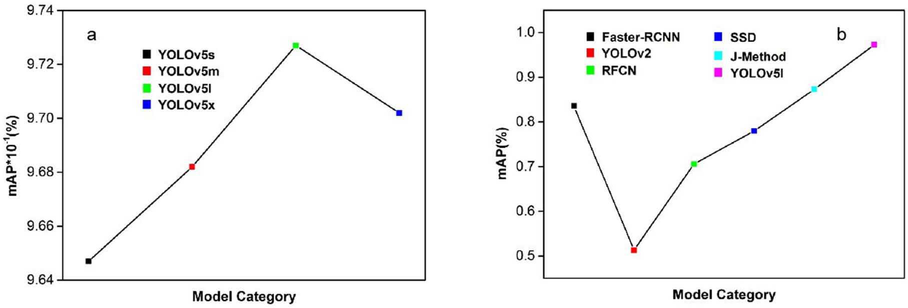

Fig. 5. a) The mAP value of the four models of YOLOv5s, YOLOv5m, YOLOv5l and YOLOv5x, b) Comparison of mAP value of YOLOv5l and J-Method.

5 Conclusion

In short, based on the existing In-D, the yolov5 algorithm is applied to the identification of insulators in transmission lines, which solves the problem of low recognition rate and low mAP value. The experimental results show that the mAP of the trained model is 11.41% higher than that of J-Method and 37.25% higher than the average of the other four methods mentioned by J-Method. That provides a new idea for the identification of insulators in transmission lines.

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Conflicts of Interest. The authors declare that they have no conflicts of interest about this paper.

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