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# Research on Defect Detection of Electric Energy Metering Box Based on YOLOv5

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# Research on Defect Detection of Electric Energy Metering Box Based on YOLOv5

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**Abstract—**The manual inspection for the damage state of the electric energy metering box consumes a lot of time, the workload is large, and the data storage is difficult. In order to solve these problems, this paper proposes an automatic detection method for the damage state of the electric energy metering box based on the YOLOv5 algorithm. The actual metering box pictures taken by the operation and maintenance inspectors are used as the training set, LabelImage is used to annotate the data set, and YOLOv5s model is used to train the data set. The experimental results show that the method proposed in this paper can accurately mark the position of the metering box lid and accurately predict its damage state. The average accuracy reaches 98%, which can meet the requirements for the detection accuracy of the power metering box damage state in the operation and maintenance inspection work.

## 1. Introduction

With the continuous expansion and development of power networks, higher requirements are put forward for power operations and maintenance [1-2]. Inspections are an indispensable part in the discovery, elimination, and maintenance of power grid defects. The quality of inspections is directly related to the safety of the power network and the reliability of power supply [3]. Therefore, improving the automation level and work efficiency of inspection management has higher economic and social benefits.

At present, the inspection results of electrical equipment can only be briefly recorded by paper worksheets. Due to the large amount of inspection work and long working hours, the recording of inspection results becomes tough, and even directly leads to low quality of inspection work. Meanwhile, the data information obtained by the inspection can-not be completely preserved and used, which makes such an important work often weak because of the lack of efficient technical method. With the development and application of deep learning target detection algorithms, new ideas and methods are provided for improving power inspection work [4,5]. The You Only Look Once (YOLO) algorithm can identify and locate the target position in the image very quickly [6-8]. Compared with the previous YOLO series algorithm, the YOLOv5 has been greatly improved in positioning accuracy and detection time [9]. Therefore, this algorithm has the potential to be used in power inspections to identify and record the health status of equipment, which greatly improves the quality and efficiency of inspections.

In order to improve the efficiency of the inspection for the electric energy metering box, this paper proposes an automatic defect detection method for the electric energy metering box based on the YOLOv5 algorithm. The actual metering box pictures are used as training sets, and the LabelImage software is used to annotate the training sets. Finally, the experimental identification results and the practical application value of this method are analyzed and discussed.

## 2. YOLOv5 target detection algorithm

YOLOv5 is the latest real-time target detection algorithm in the current YOLO series [10]. While inheriting the advantages of the YOLOv4 algorithm, it has also been optimized in aspects such as the backbone network. YOLOv5 transmits each batch of training data by the data loader and simultaneously enhances the training data. The data loader includes three data enhancement methods, including image adaptive scaling, color space adjustment and mosaic enhancement, which makes the detection accuracy of small targets and the detection speed have been improved.

The YOLOv5 target detection algorithm contains 4 models, namely YOLOv5s, YOLOv5m, YOLOv5l and YOLOv5x. Compared with the other three models, YOLOv5s model has the smallest memory and the fastest detection speed. Therefore, YOLOv5s is selected as the detection model in this paper.

Figure 1 shows the network structure of the YOLOv5 target detection algorithm, which mainly includes 4 general modules, namely: Input, Backbone, Neck and Head Output.

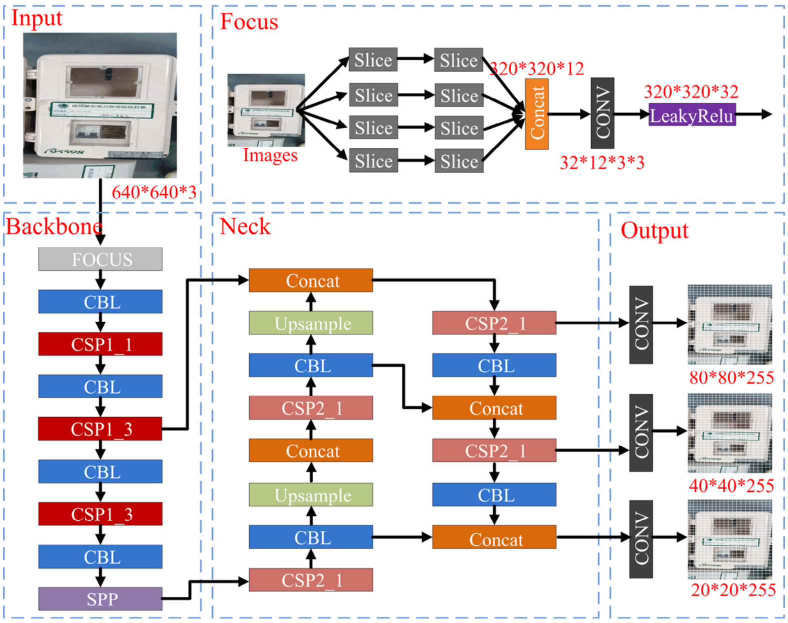

Fig.1 The network structure of YOLOv5

The input module represents the input image. The size of the input image of the network is 640*640. This stage contains the image preprocessing, that is, the input image is scaled to the input size of the network, and the normalization operation is performed. In the network training stage, the Mosaic data enhancement operation is used to improve the training speed of the model and the accuracy of the network. An adaptive anchor frame calculation method and an adaptive image scaling method are also used in the training stage.

The Backbone module usually represents some classifiers with excellent performance. This module is used to extract the features of the picture. YOLOv5 not only uses the CSPDarknet53 structure, but also uses the Focus structure as the reference network. The Focus structure contains a slice operation. Take YOLOv5s as an example, if the size of the input picture is 640*640*3, it will become a 320*320*12 feature map after the Focus structure, and after 32 convolutional layers, it will become 320*320*32 feature layer.

The Neck module is located between the Backbone module and the Head Output module. It contains Path Aggregation Net (PANet) and Space Pyramid Pooling (SPP) modules. PANet aggregates high-level feature information with the output features of different layers of CSP modules from top to bottom, and then aggregates shallow features through a bottom-up path aggregation structure [11]. Therefore, the image features of different layers are fully integrated. The SPP module uses 4 cores of different sizes for maximum pooling operation, and then performs tensor splicing.

## 3. Test Results and Discussions

### *3.1. Description of data set*

The actual electric energy metering box pictures taken by operation and maintenance personnel are selected as the data set, which contains a total of 120 pictures of metering boxes with undamaged lids and damages lids, as shown in Figure 2. The data set is expanded by 5 times through image rotation, brightness change, and noise addition, to a total of 600 pictures. LabelImage is used to mark the damage state of the lid on the measurement box, where the damaged lid on the measurement box is annotated “defect”, and the undamaged lid is annotated “no defect”. The data set is divided into training set and test set according to the ratio of 8:2.

(a) Undamaged lid (b) Damaged lid

Fig.2 The data set of metering box picture

### *3.2. Network training*

The algorithm of this experiment is based on Python and Pytorch framework. The CPU is Intel i5 8265U, the memory is 8 G, and the operating system is Windows 10. Yolov5 has already set the hyperparameters for training the Coco and Voc data sets, and our experimental algorithm continues to use its initialization parameters. The parameter is trained by the SGD optimization algorithm. The training parameters are set as follows: the batch size is 16, the maximum number of iterations is 100, the momentum factor is 0.937, and the weight attenuation coefficient is 0.0005. The dynamic adjustment of the learning rate adopts the cosine annealing algorithm, the initial learning rate is 0.01, and the cosine annealing hyperparameter is 0.2. GIOU Loss [12] is used as the loss function, the box loss coefficient is 0.05, and the classification loss coefficient is 0.5.

The train batch used for training is shown in Figure 3, in which the box marked with “0” indicates that the lid of the metering box is damaged, and the box marked with “1” indicates that the lid of the metering box is undamaged.

Fig.3 Train batch

The value of loss function, accuracy, recall, and mean average precision (mAP) of the algorithm on the training set are shown in Figure 4. Box and val Box respectively represent the average loss of the box drawn in the training set and the validation set. It can be found that as the epoch increases to 100, the loss value of the drawn box is lower than 0.04, which can explain that the accuracy of the box drawn by the algorithm is relatively high. Objectness and val Objectness respectively represent the average loss of target detection in the training set and validation set. It can be found that the target

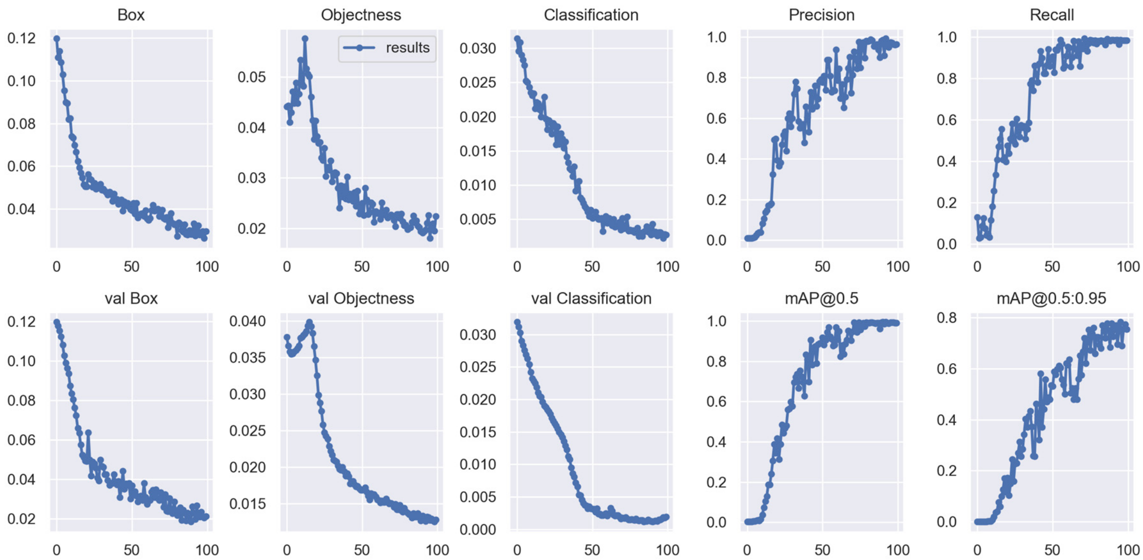


Fig.4 The train results of YOLOv5s

detection loss value of the training set is finally about 0.02, and the target detection loss value of the verification set is less than 0.015. Classification and val Classification respectively represent the average value of the target classification loss in the training set and the verification set, and it can be found that the final loss value of both is lower than 0.005. Precision represents the variation of accuracy with epoch during training, where Precision=TP/(TP+FP). TP represents the number of samples that the classifier considers to be positive and indeed positive, and TP+FP represents the total number of samples that the classifier considers to be positive. It can be found that the final precision reaches about 98%. Recall represents the change of recall rate with epoch, where Recall=TP/(TP+FN), TP+FN represents the number of samples that are indeed positive. It can be found that recall eventually reaches about 99% during the training process. mAP@0.5 and mAP@0.5:0.95 respectively represent the area enclosed by the two axes of Precision and Recall when the judgment threshold IoU is 0.5 and IoU is 0.5:0.05:0.95, which represents the average accuracy of all categories. It can be found that when IoU is 0.5, the final average accuracy is about 99%.

### *3.3. Test Results*

The trained model is tested, and the test results are shown in Figure 5. It can be found that the model can accurately predict the damage state of the metering box. When there are multiple lids on the metering box, the model can also accurately mark the position of the lid area in the figure and predict the damage state. It can be found from the figure that the box drawn by the model is in good agreement with the actual lid area. The detection confidence of the undamaged category is up to 86%, and the detection confidence of the damaged category is slightly higher than that of the undamaged category, the highest confidence is 89%. The test results are satisfactory, and it can meet the requirements of maintenance, operation and maintenance.


Fig.5 The test results of YOLOv5s

## 4. Conclusion

Based on the results and discussions presented above, the conclusions are obtained as below:

(1) The YOLOv5s metering box damage detection model constructed in this paper can accurately mark the position of the lid area on the actual metering box surface.

(2) The method proposed in this paper can accurately predict the damage state of the lid on the metering box, and the test results are satisfactory.

(3) The average accuracy of this method is as high as 98%, which can meet the actual requirements for the detection accuracy of the damaged state of the electric energy metering box.

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