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Defect Detection Method of PCB Based on Improved YOLOv5

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Abstract: *Stimulated by the increasing demand for electronic equipment, the global PCB market is expanding rapidly, and the detection of PCB defects is becoming more and more important. However, the small target, dense and other problems that are difficult to detect pose a great challenge to the accuracy and real-time performance of PCB defect detection. In this paper, YOLOv5 algorithm is applied to the field of PCB defect detection, and the corresponding YOLOv5-SlimNeck lightweight network is adopted. The experiment shows that YOLOv5l6 can detect all kinds of small and dense defects of PCB, with mAP.5 reaching 95.4%. On the other hand, YOLOv5-SlimNeck reduced the parameters by 89.6% and mAP.5 reached 94%. Compared with the lightweight network yolov5s6 in the official library, YOLOv5s6, YOLOv5-SlimNeck has only 64.5% parameters, and mAP.5 is 2.4% higher than YOLOv5s6.*

Keywords: *PCB; defect detection; YOLO*

1. Introduction

PCB will be affected by factors such as raw materials, temperature, operation equipment, etc. in the production process, which will inevitably lead to various defects. If these defects are not detected in time, they will leave hidden dangers in the subsequent use, thus causing greater economic losses. Therefore, it is of great significance to detect the defects of PCB in the production process[1].

Because of the high precision of PCB, its pads, holes, rings and traces are very small and densely arranged, which limits the traditional machine learning target detection method based on sliding window. With the rapid development of deep learning technology in recent ten years, the target detection model based on deep learning has been put forward and improved. There are two types of target detection models: one is two-stage model, such as RCNN[2], Faster-RCNN[3], etc. Second, the one-stage model, such as YOLO[4] series, RetinaNet[5], etc. Among them, the two-stage model has a high detection accuracy, but the model is too big and the detection speed is too slow, while the one-stage model can meet the demand of rapid detection of a large number of PCB boards in factories. Moreover, YOLOv5 model uses SiLU activation function and the introduction of Anchor mechanism to greatly improve the detection accuracy.

YOLOv5[6] is one of the best detection algorithms at present, and many researchers at home and abroad have applied it to various detection fields. Zhang Yue[7], etc. applied YOLOv5 to safety helmet detection in the job site;Mathew[8] et al. applied YOLOv5 to the disease detection of sweet pepper leaves. In this paper, YOLOv5 is applied to the field of PCB defect detection, and the corresponding YOLOv5-SlimNeck lightweight network is adopted. On the PCB_DATASET data set published by Peking University, the experiment shows that YOLOv5l6 can better detect all kinds of small and dense defects of PCB, while YOLOv5-SlimNeck achieves the accuracy similar to the original model on the premise of greatly reducing the parameters of YOLOv5l6 model, and it is smaller and has better performance than YOLOv5s6 model.

2. YOLOv5l6 algorithm

In 2020, Glenn Jocher, et al. improved the YOLOv4 algorithm and put forward YOLOv5 model. Subsequent researchers constantly adjusted the v5 structure, resulting in various versions[9]. YOLOv5l6 takes New CSP-Darknet53 and SPPF as the backbone, New CSP-PAN as the neck,the head is the same as YOLOv4's head. Different from YOLOv4,YOLOv5l6 chooses SiLU function as the activation function of the model, which improves the regularization effect of the network and makes the training

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more stable. The original SPP module is improved to SPPF module, which is functionally equivalent, but has higher computational efficiency. To further integrate multi-scale information and solve the multi-scale problem of the target, YOLOv5l6 also added CSP structure in PAN. The specific structure is shown in Figure 1.

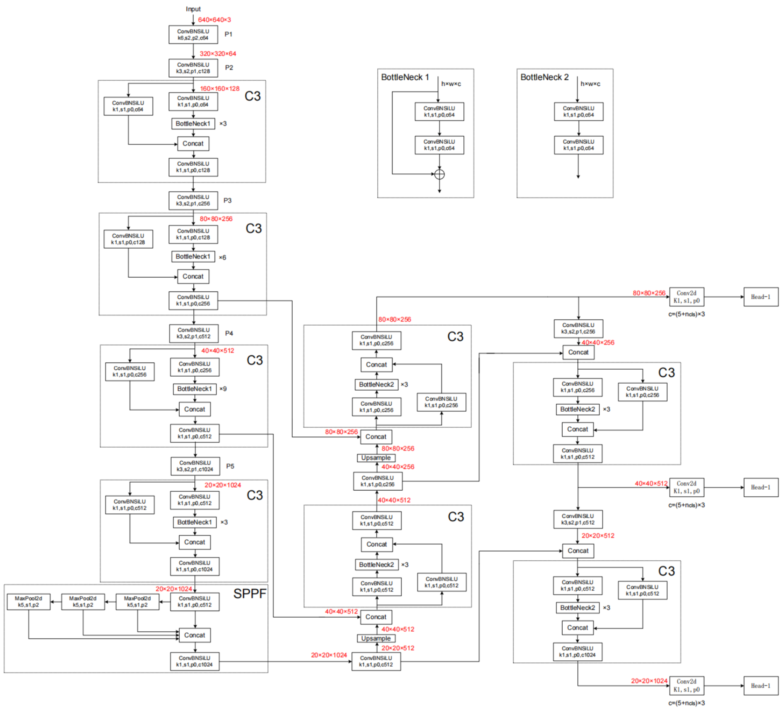

Figure 1: YOLOv5l6 model structure

Compared with YOLOv4, YOLOv5l6 has faster forward inference speed and better detection effect on multi-scale targets. In the field of PCB defect detection, the text verifies whether YOLOv5l6 model can achieve high detection accuracy, and whether its lightweight YOLOv5-SlimNeck[10]model can still maintain similar detection accuracy.

3. YOLOv5-SlimNeck algorithm

In order to keep the detection accuracy as close as possible to the original model on the basis of lightweight model, YOLOv5-SlimNeck made three improvements to the neck part of YOLOv5l6: First, a new convolution method GSConv was proposed to replace the original standard convolution; Secondly, the SlimNeck structure is designed.

3.1 GSConv

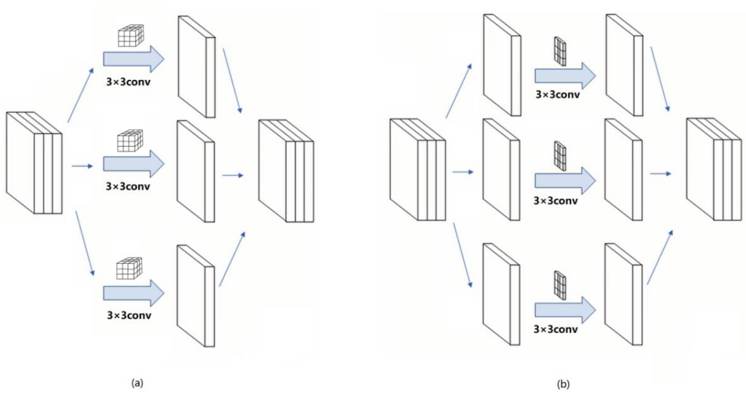

Figure 2: Schematic diagram of convolution calculation process

Figs. 2(a) and (b) show the calculation process of standard convolution (SC) and Depthwise

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Convolution(DC) respectively. Although the computation of Depthwise convolution is much smaller than that of standard convolution, it only fuses spatial information but does not fuse information between channels, so the model performance is very poor. To solve this problem, Xception and MobileNet introduced Pointwise Convolution on the basis of DC, and proposed Depthwise Separable Convolution (DSC). In the deep separable convolution, the computation is mainly concentrated in Pointwise Convolution. In order to further reduce the computation of Pointwise Convolution and lighten the network model, ShuffleNet adopts group convolution and channel shuffle to realize the information fusion between channels. However, whether Pointwise convolution or channel shuffle is used, the information fusion effect between channels is not as good as that of standard convolution. In order to approach the convolution performance of SC as much as possible, yolov5-SlimNeck proposed a new convolution method:GSConv, as shown in Figure 3.

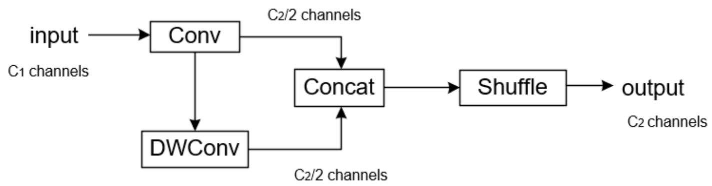

Figure 3: GSConv structure diagram

GSConv combines SC with DC, and then uses channel shuffle to evenly infiltrate the information generated by SC into DW.

3.2 SlimNeck

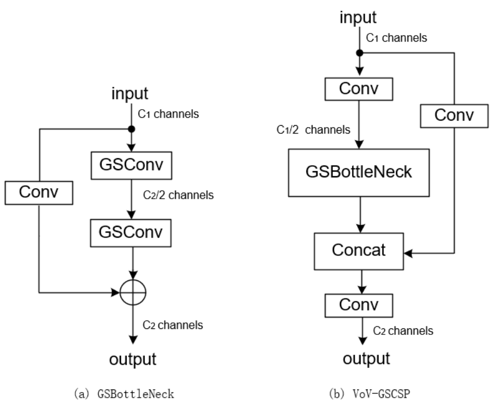

Figure 4: Structure diagram of GS Bottleneck and VoV-GSCSP

On the basis of GSConv module, GSBottleneck module and VoV-GSCSP module (Figure 4) are further proposed, which are flexibly used in Neck. The specific SlimNeck structure is shown in Figure 5.

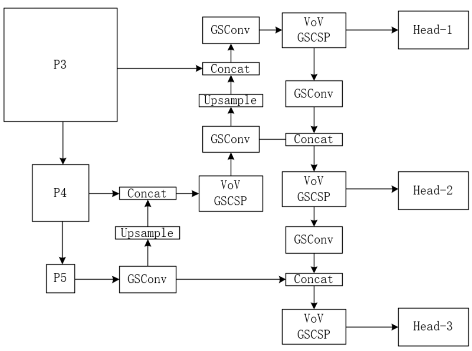

Figure 5: SlimNeck structure diagram

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4. Experimental process and analysis

4.1 Experimental data set

The data set used in this paper is PCB_DATASET published by Peking University. The data set[11]contains 693 images and corresponding annotation information. The defect points in the data set are divided into six categories: missing_hole, mouse_bite, open_circuit, short, spur and spurious_copper. In this paper, the PCB_DATASET data set is divided into training set, validation set, and test set in a ratio of 18:2:5.

4.2 Experimental environment and evaluation index

The hardware configuration of this experiment is: CPU: 4-core Intel (R) Xeon (R) silver 4110 CPU @ 2.10GHz;GPU:RTX 2080 Ti ;Memory: 15GB;Video memory: 11GB.The software environment is: Windows operating system, python 3.8, Python 1.7.0.In order to improve the convergence speed of the network, the stochastic gradient descent (SGD) algorithm is used to learn and update the network parameters in the process of network model training.Set the network parameters as shown in Table 1.

Table 1: Network training parameters

Training parameter name	Parameter value
Initial learning rate	0.01
Final learning rate	0.0001
momentum	0.937
Image input size	640×640
Batch size	8
epoch	600

In this paper, the performance of the model is evaluated from the aspects of recall, precision and mean Average Precision (mAP). The calculation formula of recall and precision is as follows.

$$recall = \frac{TP}{TP+FN} \tag{1}$$

$$precision = \frac{TP}{TP+FP} \tag{2}$$

TP (true positive) is the number of positive samples correctly identified;FN (false negative) is the number of positive samples that are wrongly identified;FP (false negative) is the number of times that a positive sample is detected but not a positive sample.

Mean Average Precision is a common detection accuracy index in target detection task, which is to take the mean value of all kinds of AP.In fact, all kinds of AP values are pr curves made by recall and precision in the experimental results, and the area value under the curve is the AP value.The mathematical formula can be expressed as follows.

$$\mathrm{AP} = \int_0^1 \mathrm{precision(recall)\ drecall} \tag{3}$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{4}$$

4.3 Performance analysis of each model

In order to understand the performance of each model in PCB defect point detection task and the performance differences among the models, the training results of the models were compared, as shown in Table 2 and table 3.

Table 2: Model comparison

Model	Precision	Recall	mAP.5	mAP.5:.95	Model size
YOLOv5l6	**0.972**	0.922	**0.954**	**0.517**	146.1MB
YOLOv5-SlimNeck	0.941	**0.926**	0.94	0.479	**15.7MB**
YOLOv5s6	0.916	0.893	0.916	0.452	24.0MB

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Table 3: Comparison of target AP

Target category	YOLOv5l6	YOLOv5-SlimNeck	YOLOv5s6
missing_hole	**0.995**	**0.995**	**0.995**
mouse_bite	0.934	**0.955**	0.908
open_circuit	**0.995**	0.935	**0.995**
short	0.985	**0.993**	0.957
spur	**0.889**	0.859	0.859
spurious_copper	**0.928**	0.903	0.784

As can be seen from Table 2, YOLOv5l6' s mAP is as high as 95.4%, which can well complete the task of PCB defect detection; However, YOLOv5-SlimNeck, as a lightweight model of YOLOv5l6, still maintains a high detection performance on the basis of greatly reducing the model scale, with a mAP of 94%, which is smaller and better than the YOLOv5s6 model in the official library (2.4% higher mAP). It is worth noting that the recall index of YOLOv5-SlimNeck is improved by 0.4% compared with the original model. Considering the harmfulness of defective point detection, the recall index should have a higher weight than other indexes. In other words, the improvement of the recall index of YOLOv5-SlimNeck compared with YOLOv5l6 is of great significance.

Table 3 shows the detection performance of each model on various defect points. It can be found that YOLOv5l6 and YOLOv5-SlimNeck have very high detection performance for missing_hole defects. On open_circuit and spurious_copper, the performance of YOLOv5-SlimNeck dropped slightly; Compared with YOLOv5l6, YOLOv5-SlimNeck has improved performance in two categories: mouse_bite and short.

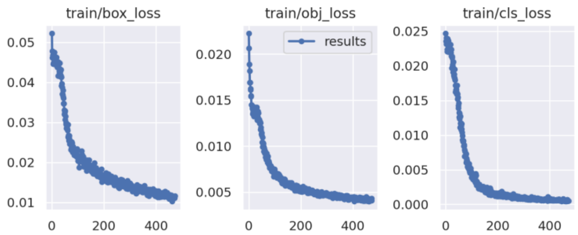

Figure 6: YOLOv5l6 Loss Diagram

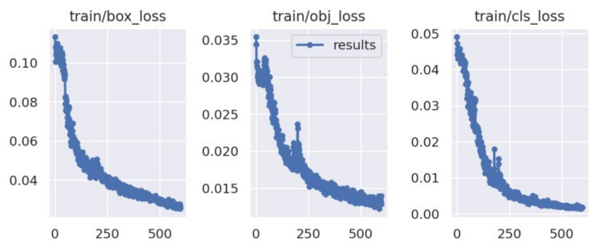

Figure 7: YOLOv5-SlimNeck Loss Diagram

Fig. 6 and fig. 7 are the loss diagrams of YOLOv5l6 and YOLOv5-SlimNeck models, respectively. Box_loss is the position loss, which measures the accuracy of the prediction of the annotation box. Obj_loss is the target loss, which measures the accuracy of the prediction of whether there is a target or not. Cls_loss is the category loss, which measures the accuracy of the prediction of the category of defect points. As can be seen from Figures 6 and 7, with the increase of training rounds, all losses are continuously reduced until convergence.

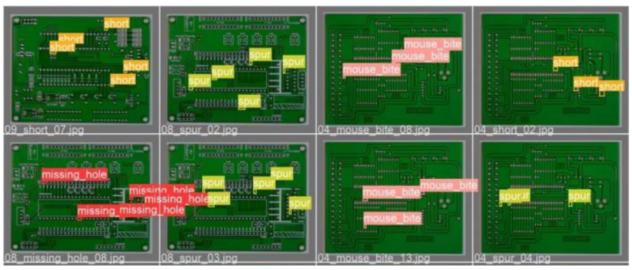

Figure 8: YOLOv5l6 Actual Test Effect

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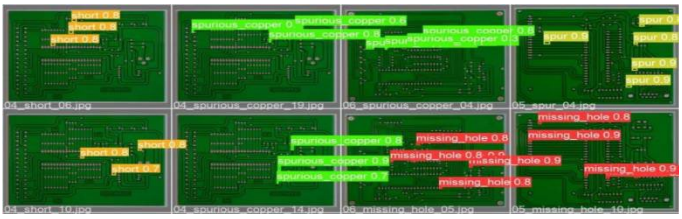

Figure 9: YOLOv5-SlimNeck Actual Test Results

Fig. 8 and fig. 9 are the actual inspection diagrams of YOLOv5l6 and YOLOv5-SlimNeck, respectively. It can be seen from the figures that YOLOv5l6 and YOLOv5-SlimNeck can detect the defects of PCB well.

5. Conclusion

In this paper, YOLOv5 is applied to the field of PCB defect detection, and the corresponding YOLOv5-SlimNeck lightweight network is trained. Experiments on printed circuit board dataset PCB_DATASET show that YOLOv5l6 can complete the defect detection task of PCB very well. YOLOv5-SlimNeck achieves an accuracy similar to that of the original model on the premise of greatly reducing the parameters of Yolov5V6 model, and it is smaller and has better performance than the YOLOv5s6 model in the official library.

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