PCB Defect Detection Using Deep Learning Methods

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***Abstract*—As a component widely used in electronic products, Printed Circuit Board(PCB) plays an extremely important role in our life. Due to technical limitations, PCB with defects will inevitably appear in the production process. In order to ensure high yield and save labor cost, this paper applied two kinds of target detection network to PCB defect detection and classification tasks. Experiments show that the two methods used in the two different distribution of data sets achieved high accuracy.**

***Index Terms*—printed circuit board, defect detection, object detection networks**

I. Introduction

PCB has a high market share in electronic components, and almost all electronic devices use it. However, in the production process of PCB, due to the limited technology, the 100% quality rate cannot be guaranteed, sometimes the produced products will have short circuit, circuit break, burr and other defects, how to screen out unqualified products and make the final product quality reliable has become an urgent demand of the PCB industry. To date, most companies PCB production line adopts the AOI [1] equipment combined with artificial visual inspection method, but the high-end equipment expensive prices and artificial cost increase the cost of enterprise, the other AOI pixel level comparison were used to detect more time-consuming, high rate of false positives, artificial detection learning cycle is long, short working time, high miss rate. Compared with this kind of high cost and low efficiency detection method, enterprises prefer to have a low cost and high efficiency automatic PCB defect detection system. In this system based on computer vision, the corresponding image processing algorithm is very important. Traditional image processing and detection algorithms mostly need to manually select features, and the selection of sliding window is also tedious and time-consuming, unable to achieve real-time detection, and the detection accuracy is not high. Since the revival of the popularity of convolutional neural network, a series of algorithms on image processing and detection have emerged. These methods are more efficient, effective and real-time than traditional methods through deep network learning features. In this paper, we apply the target detection network, which has achieved good results on PASCAL and other public data sets, to PCB defect detection, and obtain good results through experiments. In conclusion, the main contributions of this article can be summarized as follows:

- This paper applies the target detection network of deep learning to the detection of PCB.
- The method used in this paper is faster and better than the traditional image processing method.
- The experiment on two different distributed data sets once again verifies the reliability of the target detection network.

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II. Related work

Like most machine learning methods, object detection methods have undergone a change from traditional methods to deep learning methods. 2008 years ago, the method of target detection are manually selected features, combined with the sliding window method to detect and locate the target, more classic algorithm such as VJ algorithm, HOG algorithm, DPM algorithm, etc., but traditional methods have many shortcomings, such as the traditional method of design features is difficult, the different distribution of data is not applicable, not robust, efficiency is also very poor. Since 2012, when Alexnet [2] achieved very good results in ILSVRC2012, convolutional neural network has once again come into public view. The target detection algorithm based on deep learning utilizes convolutional neural network to automatically select features, which replaces the manual design features of traditional methods. The improvement of feature selection method is of milestone significance. Therefore, based on the above ideas, RCNN, SPPNet, Fast RCNN and other network structures were proposed after 2012. However, although the method of feature selection has been improved, the method of extracting the target area in the search box is still the same as the traditional method, so there is still a bottleneck in the speed of these methods. Until Faster RCNN was proposed, it used RPN network instead of the previous sliding window strategy, which greatly improved the detection speed and marked that the target detection method based on deep learning completely completed the end-to-end process. Later, YOLO [3], SSD [4] and FPN [5] networks have been far superior to traditional target detection algorithms in terms of performance and speed.

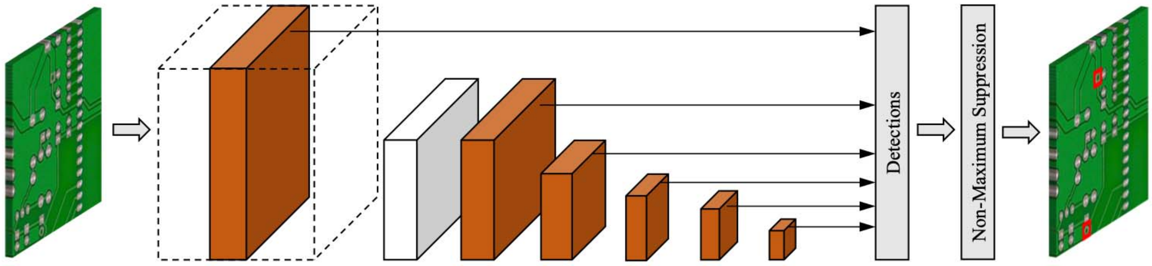


Fig. 1: The network structural of SSD.

The target detection algorithm based on deep learning has been applied in face detection, pedestrian and vehicle detection, object detection, text detection, defect detection and other aspects.

J. Li et al. [6] improved the YOLO network and made it all convolutional. The experiment shows that the improved network, which includes 27 convolution layers, is very fast and effective in the surface defect detection of steel strip. H. Lei et al. [7] applied Faster r-cnn network to the detection task of polarizer defects. The experimental results showed that the target detection network with deep learning could solve the problem of polarizer image quality well, complete detection quickly, locate and mark defects accurately. W. Hou et al. [8] used the model based on deep neural network to learn the intrinsic features of the image, and used the sliding window method to detect the image. Their results showed that the classification model was effective in detecting the quality of welded joints. Y. Li [9] et al. adopted SSD as meta structure, combined with mobilenet network to form mobilenet-ssd, proposed a surface defect detection method based on this network structure, realized the typical defect detection of container sealing surface on the production line, and provided a new idea for optimizing actual industrial production. H. Lin [10] et al. introduced the application of reel neural network in the detection of LED chip defects and realized the detection and location of it.J. Lin et al. proposed a robust detection method based on visual attention mechanism and feature graph deep learning, which solved the problems of false inspection and missing inspection of castings in the production process. M. Nasrollahi et al. [11] proposed a method for the detection of concrete surface defects using deep neural network, and explored a new idea for improving the security of infrastructure system. S. Mei et al. [12] proposed an automatic method based on unsupervised learning to detect and locate defects in fabrics, which solved the problems of low efficiency, low accuracy and difficulty in adapting to industrial applications of traditional fabrics. Experimental results also show that the proposed method has good performance and effectiveness.

III. Objects detection networks

This part mainly introduces the network structure used.

A. SSD

SSD algorithm is a typical algorithm of one-stage deep learning series of target detection algorithms. It was proposed by liu wei in ECCV in 2016. It uses the direct regression method to obtain the category and location of the target, which can be predicted on the feature maps of different scales. Even if the image resolution is relatively low, the detection accuracy can be guaranteed. Its network structure is shown in figure 1.

The SSD backbone network USES VGGNet(VGG16), and then selects the output of six layers in the network for multi-scale Feature Map prediction, which is used as the input of the prediction layer, and finally uses NMS to merge and filter the results.

B. FPN

Faster r-cnn is one of a series of algorithms for deep learning object detection in a typical two-stage mode. Compared with the previous network structure and algorithm, its innovation lies in the use of Shared convolution and the addition of RPN structure. The whole network is also an end-to-end structure, and the computing efficiency is much higher than that of Fast r-cnn. The original Faster r-cnn network includes the backbone network, RPN network and ROIPooling layer to classify the target and precisely locate the position. In the RPN network, background and foreground separation and preliminary target positioning are mainly completed. The ROIPooling layer can be used to process the output in the RPN network and input it into the subsequent sub-network for detailed determination of the target category and refinement of the position, so as to obtain the final output. FPN network structure is mainly based on this improvement, that is, the operation of adding deconconvolution layer and lower sampling layer is used in the backbone network. In this paper, resnet101 is used in the backbone network.

IV. Experiments

We used two experimental data sets. One is the open data set provided by the intelligent robot open laboratory of Peking University. The name is printed circuit board defect data set. The other is DeepPCB, a PCB defect detection data set provided by researchers from Shanghai jiao tong university on GitHub. The experimental structure shows that the two network models we used detect and locate defects on both data sets, and classify defect types, obtaining high accuracy.

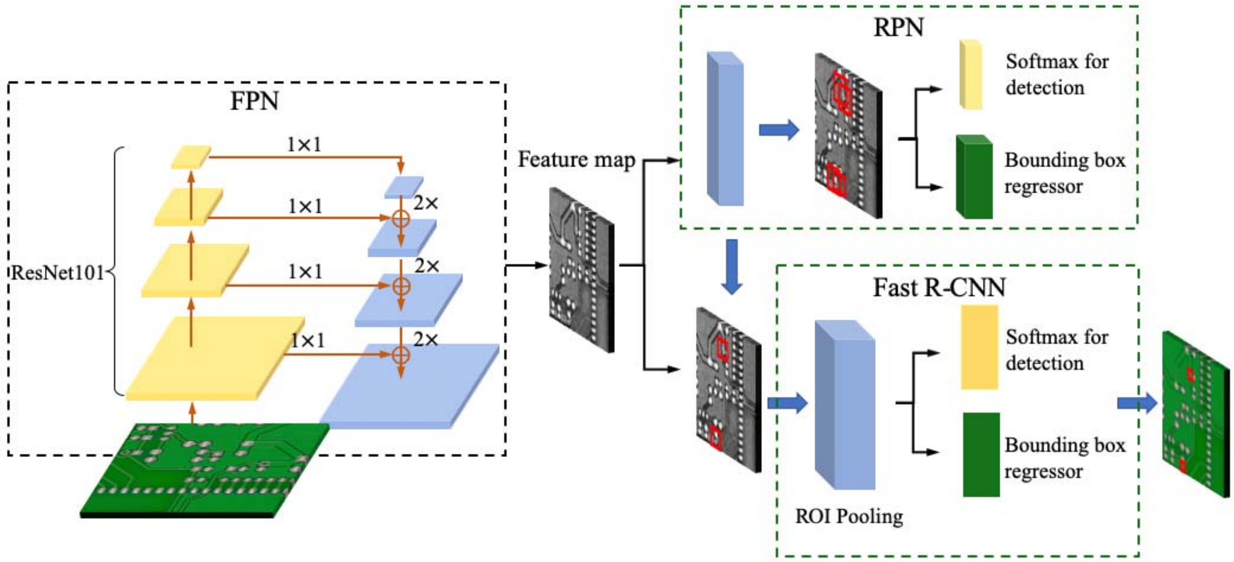


Fig. 2: The network stuctural of FPN.

A. Datasets Description

1) PCB Dataset: This is a public synthetic PCB dataset containing 1386 images with 6 kinds of defetcs (missing hole, mouse bite, open circuit, short, spur, spurious copper) for the use of detection, classification and registration tasks.

2) DeepPCB Dataset: a dataset contains 1,500 image pairs, each of which consists of a defect-free template image and an aligned tested image with annotations including positions of 6 most common types of PCB defects: open, short, mousebite, spur, pin hole and spurious copper.

B. Evaluation Metrics

In the target detection task, after the image to be tested is input, the model will output a series of prediction boxes, that is, the possible defect positions on the image predicted by the model. How to evaluate the accuracy of prediction depends on the evaluation index. Usually we use the IOU to determine whether the prediction box and the real box are the same, as shown in Fig. 3.

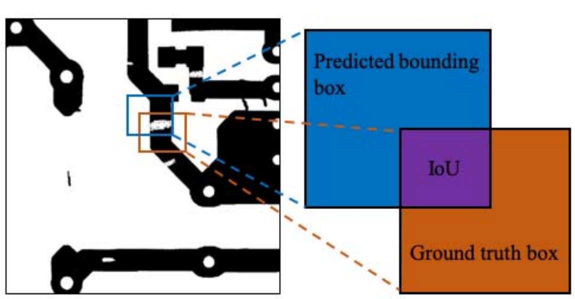


Fig. 3: Example of a figure caption.

The definition of an IOU can also be expressed as 1.

$$IoU = \frac{Area\ of\ overlap}{Area\ of\ union} \tag{1}$$

In the experiment, we set the value of IoU to 0.5, that is, when the crossover ratio reaches 0.5, we believe that the prediction box and the real box are the same box, which also means that the position of the prediction box is correct. In addition, methods such as precision-recall curve(PRC), average precision(AP) and F1-score are also used to evaluate the results of target detection. TP means the number of positive samples predicted to be positive samples, and TP means the number of negative samples predicted to be positive samples. Accuracy is the ratio of TP to their sum, as defined in 2.

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

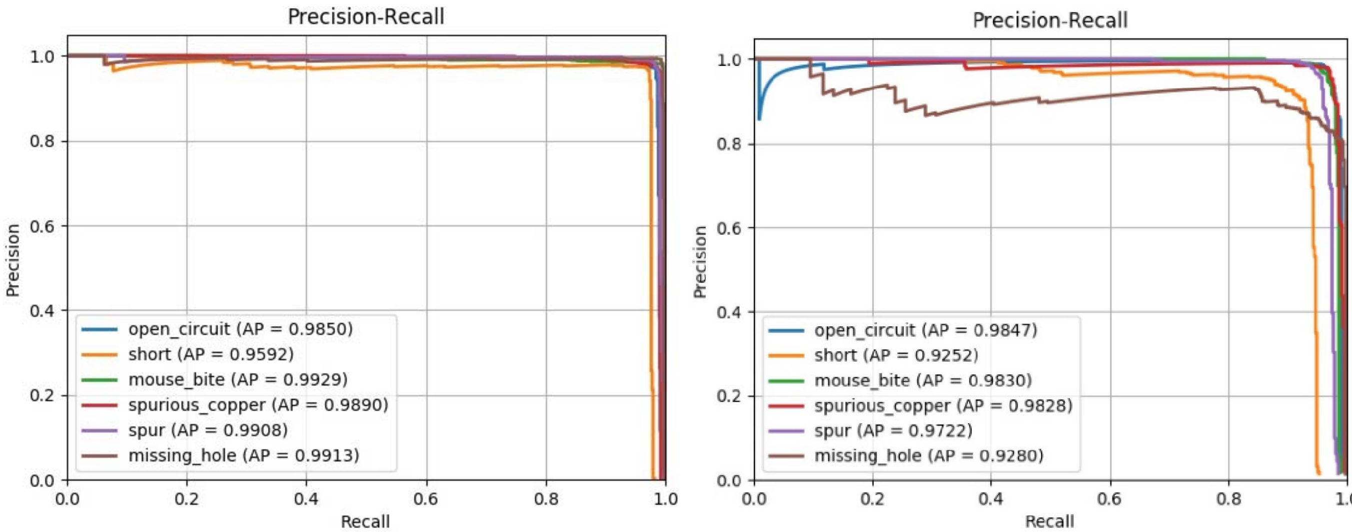
FN represents the number of positive samples predicted to be negative samples, and the definition of recall rate is shown in 3.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

We can see from 2 and 3 that precision reflects the model's ability to distinguish negative samples. The higher its value, the stronger the model's ability to distinguish negative samples. Recall reflects the model's ability to recognize positive samples. The higher its value, the stronger the model's ability to recognize positive samples. In order to integrate their different characteristics, we also used the index f1-score, which is a comprehensive consideration of precision and recall. The higher its value is, the more robust the classification model is.Its formula definition is shown in 4.

$$Recall = \frac{2TP}{2TP + FN + FP} = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{4}$$

We will use these indicators to evaluate the performance of the model in subsequent experiments.



(a) Case I (b) Case II

Fig. 4: Simulation results for the network.

C. Experimental Results and Comparisons

Table I shows the experimental results of SSD model and FPN model on two data sets. We calculated the accuracy rate, recall rate and f1-score, respectively. It can be seen from the experimental results that the two models have achieved good results on data sets with different distributions. From the experimental results, we can see that the network with FPN structure has a good detection effect on both PCB data sets, the detection effect of SSD is slightly worse than that of FPN, and the value of f1-score is only 54.4% on the PCB Dataset.

TABLE I: THE EXPRIMENTAL RESULTS

Method	**Evaluation Index**	**Dataset Name**	
		PCB Dataset	DeepPCB Dataset
SSD	Precision	98.9	89.7
	Recall	54.4	78.5
	F1-score	70.2	83.7
FPN	Precision	96.4	92.7
	Recall	98.2	97.3
	F1-score	97.3	94.6

V. CONCLUSION

We put the two classic target detection algorithm is applied in the PCB defect detection task, the experimental results show that the two kinds of target detection based on deep learning network in the distribution of the two different data sets obtained very good effect, which better FPN network, in part because FPN used the inverted pyramid structure, the structure of small target detection is more suitable. Future work could improve the current SSD network by adding a similar deconvolution layer and adding it to the previous layer to explore the effect of this structure.

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