PCB Electronic Component Defect Detection Method based on Improved YOLOV4 Algorithm

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Abstract. In an era of information, people's demand for electronic products is greatly increased. As an important part of electronic components, Printed Circuit Board (PCB) has a huge annual output and a variety of sizes and types. Therefore, the traditional method of manually detecting PCB defects may fail to meet the required production standards due to the high error rate. With the development of deep learning, a batch of PCB defect detection models combined with deep learning have been produced, which improves the detection efficiency. However, there are still some problems in these methods, such as low automation degree, low detection degree, and poor stability. This paper proposes an improved algorithm, based on YOLOV4, which uses PCB defect data set released by the Intelligent Robot Laboratory of Peking University, and has abundant images of different defect types, which greatly increases the reliability of the model. By analyzing the feature distribution of CSPDarkNet53 structure layer and the detection target defect size distribution in the data set used, in the data pre-processing and input stage, the image is automatically subdivided according to the average size of the callout box of the detection image, and the probability of anchor containing detection target is increased. Experimental results show that the improved YOLOV4 algorithm has a mean Average Precision (mAP) of 96.88%.

1. Introduction
With the development of industry 4.0 era, each country has accelerated the pace of industrialization for the development of the manufacturing industry. In the fierce competition of manufacturing industry in major countries in the world, the development of intelligent manufacturing is considered a key measure to build advantages. This trend means information technology will be widely applied and integrated within the manufacturing industry, which is also a significant feature of the information age. The electronic information industry is developing rapidly, with mobile phones and computers as the representative of the widespread popularity of electronic equipment. Printed Circuit Board is the foundation of the information industry and electronic manufacturing industry, the basic component of numerous electronic products, and the hardware carrier of electronization and informatization.
Among the key technologies of many manufacturing industries, product quality detection in the industrial environment is one of the keys. However, a large number of factories still adopt traditional manual detection as the main detection method. With the development of PCB towards high precision, high complexity and high performance, manual inspection is difficult to meet the needs of quality inspection. In order to improve the efficiency of product inspection, computer vision has gradually become a technical means to realize quality inspection. To this end, PCB defect detection aims to detect the defect using deep-learning frameworks, including convolution neural network (CNN), multiple layer perceptron (MLP), and replaces the work done by the workers. Automatic optical inspection (AOI) system is the application of machine vision technology in industrial application scene, and its system implementation is guided by the theory of machine vision technology. Compared with traditional manual detection, machine vision technology can provide higher detection accuracy, improve product quality and reduce production cost effectively. The workflow of AOI system usually includes image acquisition, preprocessing, feature extraction and detection, etc., and the system has different categories according to different item feature information [1].

Deep learning uses feature information to process data and mimic human thought processes and allows the computational model to contain multiple processing layers to learn representational data with multiple layers of abstract data. It has also promoted the development of artificial intelligence, which has been applied to industrial scenes and people's daily life in many aspects. Deep learning develops rapidly in the field of machine vision, especially in the field of object detection and recognition algorithm. In the context of rapid development of machine learning algorithms, researchers have proposed many target detection algorithms based on deep learning, which can be roughly divided into two categories.

One is the traditional target detection algorithm framework: cascade classifier Haar HOG/ACF/LBP/integral feature and Adaboost etc. [2]. If early Haar working principle is through the simple classification of assembling the strong classifier, its target detection effect is unsatisfactory. And it is almost impossible to detect the non-rigid target, like the pedestrians on the road. Based on this, scholars have put forward the histogram of oriented gradient [2] and support vector machine (HOG + SVM) structure, which can detect the target with fast speed, but it also has obvious shortcomings, such as low detection accuracy and detection recall. The Deformable Part-based Model (DPM) [3], proposed by Felzenszwalb et al. in 2008 and improved many times, has been the peak of the traditional target detection algorithm and served as an extension of HOG detector. DPM follows the detection idea of "divide and conquer". Training can be simply seen as learning a correct method to decompose objects, and reasoning can be seen as a collection of tests for different object components. This kind of traditional target detection algorithm is modified by R. Girshick to further represent the process as a special case of multi-instance learning [4]. It can detect the target with fast speed, but it also has obvious shortcomings, such as low detection accuracy and detection recall.

The second type of target detection algorithm is the machine learning algorithm represented by CNN, which has high detection accuracy and detection rate. In 2012, AlexNet shone in ILSVRC competition held by ImageNet. Inspired by this, Girshick et al. successfully transferred the technology of image classification to target detection using the method of candidate regions, and proposed RCNN [5]. In order to solve the problem of slow training speed and large training space required by R-CNN, R Girshick, the original author of R-CNN, improved R-CNN and proposed Fast R-CNN [6], which absorbed the characteristics of SPP-NET [7] and greatly improved the speed of target detection. However, such an algorithm requires a high computing capacity of the computer, so there will be low efficiency in real-time detection. In 2015, Joseph et al. proposed the YOLO [8] algorithm, which solved target detection as a regression problem and was able to predict the output of object position boundary box and category directly from the original image in a single neural network, which was a single network structure. Faced with the problems encountered by previous machine learning algorithms, Yolo algorithm has the ability to solve. In 2016, Liu et al. proposed a single shot multibox detector (SSD) [9], which followed the thoughts of YOLO and achieved target positioning and classification in one time. Meanwhile, a similar prior box was proposed based on an anchor of Faster RCNN, and a detection method of pyramidal feature hierarchy was added to achieve better detection speed and accuracy.
With the advent of YOLO algorithm, real-time detection becomes possible. The idea of YOLO is to input the whole image, calculate it through the neural network, and directly give the position and border of the object and its category in the output. YOLO does not extract and classify the candidate areas, thus shortening the processing time of the image at the expense of some detection rate.

Inspired by YOLO thought, many excellent improved algorithms have been proposed, such as YOLOv2 [10], YOLO9000 [10], and YOLOv3 [11]. While ensuring real-time performance, YOLOv3 achieves high precision and a high detection rate, and its mAP is as high as 57.9%. In the YOLOv4 [12] algorithm proposed by Alexey et al., CSP structure and PAN structure were added while maintaining the same overall architecture as YOLOv3. Compared with YOLOv3, YOLOv4 can greatly improve the detection accuracy of the model while maintaining the speed. Compared with YOLOv3, YOLOv4 has undergone many changes in network structure, which has improved the performance of the model. This is also the reason why YOLOv4 is chosen for PCB detection in this paper.

As the application of computer vision in the industrial scene, industrial component detection is one of the key technologies. As the hardware foundation of many electronic components, the application of the detection technology developed by a deep learning algorithm to PCB defect detection has important research significance. In fact, more and more attention has been paid to the target detection of PCB. With the development of deep learning, the algorithm of PCB defect detection based on machine learning algorithm has been proposed. Raj et al. first converted the image into YUV space for Gaussian filtering and median filtering, and then used the positive and negative difference method between the standard graph and the sample graph to detect defects [13]. Adibhatla et al. used the improved YOLO/CNN model designed by the YOLOv2 algorithm to detect the defects on the PCB board, achieving a high detection accuracy [14]. However, the data set they used was a graph sample generated by the AOI machine, so the model was not robust. Hu et al. established a network based on Faster RCNN to achieve production application [15]. However, the model based on it belongs to the two-stage detection algorithm, and its detection efficiency is not high in some real-time scenes.

As the PCB to the trend of high accuracy, high complexity, high performance development, PCB defect detection based on machine vision technology often needs to deal with high resolution image, and complex graphical information for testing. Therefore, some small defects may be more difficult to be detected which puts forward high demands on accuracy, in particular the real-time detection of scenarios may also require a higher detection speed. This brings great challenges to the target detection algorithm, which needs to give consideration to the efficiency and accuracy of the algorithm. This paper proposes a YOLOv4 based PCB defect detection algorithm. First, the images are resized to a fixed-size of 608 * 608. The resized image is then sent to the YOLOv4 method to generate the defect boxes with their categories. We achieve 96.88% mAP on the corresponding dataset, which outperforms other state-of-the-art detection methods. The contributions of this paper are as follows:

- We proposed a YOLOv4 based PCB defect detection method. With the PCB defect dataset released by the Intelligent Robot Laboratory of Peking University, we fine-tune the original method to significantly enhance the accuracy and robustness.
- We improve the hyper-parameter setting of YOLOv4 model to make it more suitable for PCB defect detection.
- Compared with the YOLOv4 model, the average mAP of the improved YOLOv4 model was increased from 89.60% to 96.88%.

2. Related work and method

2.1. PCB defect dataset

In the case of deep learning combined with computer vision, according to the theme of the defect inspection of PCB board, this paper uses the intelligent robot laboratory issued by Peking University PCB defect dataset, which contains 1386 images and 6 kinds of defects (missing hole, mouse bite, open circuit, short, spur, spurious copper), used for detection, classification and registration tasks. The data set classifies images with different defect types into different categories by classification. In addition,
the data set originally provided files in the format of "XML" to save the labels of defects and types in the figure, but this type of tag does not meet the requirements of the experimental model, so this experiment transformed the files in the format of saved tags into the format of "TXT" to ensure the smooth operation of the experiment. The following figure shows the image with a label. It can be found from Figure 1 that the defect is very small. According to measurements, the average size of the callout box of the defect in the figure of the data set is about 8×8 pixels. The data set used in this experiment contains PCB board images and six different types of defects on different diagrams, as shown below.

![Figure 1. Examples of input images.](image)

(a) Missing hole; (b) Spurious copper; (c) Open circuit; (d) Mouse bite; (e) Spur; (f) Short

In addition, for the consideration of the robustness of the model, the rotated image is also adopted in this experiment. The image is rotated at a certain angle through the program to improve the robustness of the model and ensure the accuracy of detection even if the image is rotated in the subsequent detection. In this experiment, the image rotated at a certain angle and its labeling defects are shown in the following figure.
2.2 Data pre-processing
The improved model in this paper uses various normalization methods to enhance the image according to the rotation provided in the data set and the translation, flip and other operations. Considering that the number of image samples is sufficient to ensure the generalization of the model, we temporarily take the randomly adjusted brightness and contrast of the image as the options for data enhancement.

2.3. Architecture of improved YOLOv4

2.3.1. Input
According to the standard proposed by Mate Kisantal et al. in 2019 [16], it can be inferred that PCB board defects in the data set images used in this experiment belong to small targets. According to the specific criteria given in the table below, the defects on the PCB board belong to small targets, so our experiments are more inclined to detect small targets. Therefore, in the input part, the improved YOLOv4 model proposed in this experiment uses Mosaic data to enhance the input side of training. By zooming, cropping and randomly arranging the adopted pictures, we can splice them more suitable for our small target detection.

The theoretical method of Mosaic data enhancement is derived from CutMix [17] that is, a part of the image area is intercepted but not filled with 0 pixels, but the area pixel values of other data in the training set used in this experiment are filled immediately. Then the classification results will be distributed according to a certain proportion.

|                | Min rectangle area | Max rectangle area |
|----------------|--------------------|--------------------|
| Small object   | 0×0                | 32×32              |
| Medium object  | 32×32              | 96×96              |
| Large object   | 96×96              | ∞×∞                |

Namely, according to the formula:
\[
\begin{align*}
\tilde{x} &= M \ominus x_A + (1 - M) \ominus x_B \\
\tilde{y} &= \lambda y_A + (1 - \lambda) y_B
\end{align*}
\]  (1)
(2)

Where \(x_A\) and \(x_B\) represent two different training samples; \(y_A\) and \(y_B\) represent the corresponding label value. \(M \in \{0,1\}^{W \times H}\) represents the filling of binary mask for the truncated part; \(\ominus\) represents
the multiplication of pixels by pixels; 1 is the binary mask with all elements of 1; \( \lambda \) belongs to the Beta distribution, and finally generates new training samples and corresponding tags \( \sim x, \sim y \).

2.3.2. Network structure of YOLOv4

The network structure of the YOLO v4 model designed and adopted in this paper is mainly composed of two parts, backbone and neck, respectively. To improve mAP index of target detector in this study, this paper selects CSPDarknet53 of Cross Stage Paritial (CSP) Network with strong image feature extraction capability and moderate scale as a backbone. SPP+PAN is selected as the neck part to fuse the feature information of feature maps of different sizes.

![Figure 3. Improved YOLO V4 model structure](image)

2.3.2.1 BackBone

Compared with the Darknet53 used by YOLO V3 as the BackBone network, the BackBone for this experiment consists of five CSP modules. The size of the convolution kernel in front of each CSP module is set as \( 3 \times 3 \), Stride=2, so that the model can realize the downsampling function. After inputting an image whose size is \( 608 \times 608 \), the feature map keeps changing in the form of: \( 608 \rightarrow 304 \rightarrow 152 \rightarrow 76 \rightarrow 38 \rightarrow 19 \). After 5 times of CSP modules, the feature map of size \( 19 \times 19 \) can be obtained.

When using the CSP module, the model divides the feature mapping of the base layer into two parts, and then combines them through the cross-stage hierarchy to reduce the computation and ensure the accuracy of the experiment. Therefore, it realizes the purpose of reducing memory cost, reducing computing bottleneck, and enhancing CNN learning ability and accuracy maintenance.

1) Mish activation function

As for the backbone, instead of the Leaky-ReLU activation function used in the previous model, the experimental model uses the Mish activation function. The fact that the positive value of the activation function can be reached to any height avoids the saturation caused by the cap, which in theory allows for a slightly negative value to yield a better gradient flow. In addition, the function is non-monotone, which helps to maintain a small negative value to achieve the effect of stabilizing the network gradient flow. In terms of practical experimental considerations, a smoother activation function, such as Mish function, is adopted to help us make better information penetrate into the neural network, so as to obtain better accuracy and generalization.
In the implementation process, \( x \), as the input data, first passes through the \texttt{softplus} stage, then enters into the Mish stage after \texttt{tanh} operation and is merged.

\[ f(x) = x \times \tanh(\texttt{softplus}(x)) \]  

\[ (3) \]

2.3.2.2. Neck Part

As the neck of the target detection network, the neck part is very critical. The model inserts a neck between the backbone and the output layer to help extract the fusion characteristics. The YOLOv4 model used in this paper adopts SPP module and FPN+PAN structure.

\textit{1) Spatial Pyramid Pooling (SPP) module}

The common convolutional neural network used in this experimental model consists of convolutional layer and full connection layer. However, the first full connection layer of CNN model requires the size of the input data, so CNN needs to fix the size of the input data. In order to solve this problem, the SPP (Spatial Pyramid Pooling) module adopted in this experiment enables the input image’s aspect ratio and size to be arbitrary.

When an image of any size enters into the input image, convolution operation is first performed on it. After the last convolutional layer acts on it, feature mapping of any size of this layer is output. After entering the layer of SPP module, the feature mapping from each previous layer was divided into 16 parts, with 256 channels and a size of \(16 \times 256\). In addition, the SPP layer can also divide the feature map into parts with specifications of \(4 \times 256\) and \(1 \times 256\). After the feature mapping is divided into equal parts, SPP will select max pooling for pooling and conduct max pooling for each part.

![Figure 4. The structure of the Neck part](image)

\textit{2) Feature pyramid network (FPN) and path aggregation network (PAN) part}

As the convolution kernel in front of each CSP module mentioned above is \(3 \times 3\) in size, the down-sampling operation especially required in the YOLOv3 model proposed earlier, is implemented. After several times of downsampling, the model outputs the feature map of \(76 \times 76\), which is then used through the FPN layer, and then goes through the PAN structure twice to output the predicted feature map, with the size of \(38 \times 38\) and \(19 \times 19\) respectively.

In other words, in this part of the experimental model, the last three YOLO layer features are as follows:

- The biggest feature of the first YOLO layer is \(76 \times 76\), corresponding to the smallest anchor box.
- The biggest feature of the second YOLO layer is \(38 \times 38\), corresponding to the medium anchor box.
- The biggest feature of the third YOLO layer is \(19 \times 19\), corresponding to the biggest anchor box.
In addition, in the PAN structure, concat (Route) is used to concatenate the tensors of the two feature maps, so that the dimensions of feature maps after fusion are changed.

Figure 5. Structure of FPN+PAN part

2.3.3 Prediction
In the prediction part, the anchor frame mechanism of the output layer was roughly similar to the previously proposed YOLOv3. The loss function CIOU_Loss is described in section 3.2.3.B during training set, and the prediction box was selected by DIoU_nms (Distance-Intersection over Union) [18], which was different from the NMS used by YOLOv3.

2.3.3.1 Bounding Box
First, K-means clustering is adopted for objects in the image. Each cell in the feature map presented can predict 3 bounding boxes, each of which predicts: (1) The position of each box, including the center coordinates $t_x,t_y$, and the height and width of the box $bh,bw$. (2) An objectness prediction. (3) Six defect categories of PCB board.

In the detection, the corresponding receptive field of the model is different each time. Because the defects on the PCB detected by this experiment belong to small targets, 8 times the receptive field is tended to be adopted, and the size of anchor boxes are (10,13), (16,30), (33,23). In the actual experiment, for the purpose of accuracy, three different receptive fields are still used to find three kinds of goals: large, medium and small. Therefore, when the matrix size is $416 \times 416$ and 10,647 proposal boxes are actually produced.

2.3.3.2 CIOU loss function
The experiment of PCB target detection in this paper adopts a loss function similar to that of traditional target detection tasks. From the classification loss and box regression loss, the CIOU loss function takes into account: Bounding area, center distance and aspect ratio.

For the consideration of overlapping area and distance of a center point, when the target box wraps the prediction box, the distance between two boxes can be measured directly to achieve faster training. Considering the aspect ratio, the model function adds an influencing factor on the basis of the previous model function, taking into account both the aspect ratio of the prediction box and the target box.

$$L = 1 - IoU + R(B,B^{gt})$$  \hspace{1cm} (4)

$$L_{CIOU} = 1 - IoU + \frac{\rho^2(b,b^{gt})}{c^2} + \alpha\nu$$  \hspace{1cm} (5)

where $R_{CIOU} = \frac{\rho^2(b,b^{gt})}{c^2} + \alpha\nu$ is defined as the penalty term of prediction box $B$ and target box $B^{gt}$;
分别代表中心点$B, B'$；$c$代表最小外矩阵的对角距离$B, B'$；$\rho(\bullet)$代表欧氏距离。作为影响因素，$\alpha \nu$考虑了预测框的长宽比以及目标框的长宽比。$\alpha$作为参数用于权衡，$\nu$作为参数用于测量方面比例的一致性。

$$
\alpha = \frac{\nu}{(1 - \text{IoU}) + \nu} \tag{6}
$$

$$
\nu = \frac{4}{\pi^2} \left( \arctan \frac{w}{h}^\prime - \arctan \frac{w}{h} \right)^2 \tag{7}
$$

3. Results

In this paper, the batch was set to 64 and the input image was cropped to the size of 608×608 pixels. We use the designed model to process the input image. A 0.0005 weight decay and a 0.949 momentum were used. The learning rate is 0.001 for 30K mini-batches. We spend 40 hours more on the entire training process.

According to the characteristics of the references and models consulted, non-maximal suppression (NMS) was adopted to reduce redundancy in this experiment's proposal area according to the classification score. The proposal areas that effectively solve some defects are highly overlapping. The IoU threshold of NMS was fixed at 0.5, leaving 4000 proposal areas for the images in the experiment.

In addition, for small target detection problems such as defect detection on PCB board, training results of other models and methods on PCB data set are compared in this paper, and the results are summarized in the table below. The model proposed by this paper is compared with the testing network proposed by other researchers, such as Faster R-CNN with backbone VGG-16 and Resnet-101. When the threshold of IoU is 0.5, the improved YOLO v4 obtains the highest mAP, which indicates the effectiveness of YOLO v4 model and the importance of a reasonable design of anchor points and multi-scale feature fusion. Moreover, it can be seen that the experimental model in this paper is more suitable for the small defect, that is, the small target, compared with the anchoring scale of Faster R-CNN.

Through experiments, the detection performance of different defect types on PCB test set can be compared, and the ability of the model to detect defects can be evaluated by drawing the Precision-Recall curve. It can be seen that the model performance of this experiment is good, with an average detection accuracy of 96.88%, which is shown in Table 2. Furthermore, the category-based results are depicted in Figure 6.

| Model            | Backbone     | Anchor | Fine-tune | mAP@0.5       |
|------------------|--------------|--------|-----------|---------------|
| Faster R-CNN [19]| VGG-16       | 2K     | Yes       | 58.57%        |
| Faster R-CNN [19]| ResNet-101   | 2K     | Yes       | 94.27%        |
| FPN [20]         | ResNet-101   | 2K     | Yes       | 92.23%        |
| YOLO v4-origin   | CSPDarknet53 | 2K     | No        | 89.60%        |
| **YOLO v4-ours** | **CSPDarknet53** | **2K** | **Yes** | **96.88%**    |
Figure 6. Precision and recall curve results based on the improved model

It can be seen from Figure 7 that the average loss of this experiment always keeps a downward trend during the experiment. When the final experimental result converges, the current average loss is about 0.3188.

Figure 7. Change of loss value of the improved model

The final test result of the experimental model will mark the parts that may be absent in the PCB image and predict the probability value. Examples of defect inspection results are presented in Figure 8.
4. Conclusion
PCB has been paid more attention to the industry, which has a large range of applications. It is essential for the factories to evaluate the quality of PCB. However, there are few algorithm models proposed in detecting the defects on PCB at present, and the accuracy and speed cannot be taken into account. How to achieve the double standard of efficiency and accuracy has always been a difficult problem in target detection. In this paper, the combination of the newly proposed YOLOv4 algorithm based on the deep learning framework and the defect detection of PCB board can achieve higher speed and more accurate detection accuracy. First, after pre-processing the data, the YOLOv4 algorithm features are used to get more accurate anchors. Moreover, various experiments are conducted on the dataset, which validates the effectiveness of the proposed method. Compared to the original YOLOv4 method, we achieve an improvement of 8.125% on mAP with the mAP of 96.88%. Based on the original YOLO network, the target features can be completely detected after the improvement, which provides the possibility for the development of object detection applications later. Moreover, our method is more suitable for the detection tasks of a small object.

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