ISSN: 2414-1895 DOI: 10.6919/ICJE.202206_8(6).0045

Multi-target Detection of PCB Defects based on Improved SSD

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Abstract

With the rapid development of computer technology, research on deep learning is progressing rapidly, defect detection based on deep learning has become a new research hotspot. As a first-order deep learning network, the SSD algorithm has made innovations from multiple angles. The use of SSD algorithm is not only a cost-saving alternative to manual labour, but also increase the speed and accuracy of detection. In this paper, we propose an improved SSD algorithm for PCB defect identification. By adding the coordinate attention mechanism module, the problem of ignoring important features of the image, which exists in the original algorithm, is solved. In the experimental tests on the self-built dataset, comparing with the original SSD algorithm, the PCB defect recognition accuracy of the improved network increased by 1.34%, the recall rate increased by 4.77% and the F1 value increased by 3.93%. Compared with other algorithms, the improved algorithm has certain accuracy and speed advantages in the engineering field and can be applied to identify defects in actual factory production.

Keywords

PCB; Defect Recognition; SSD; Coordinate Attention.

1. Introduction

Printed Circuit Board (PCB) is widely used in electronics, communications, computers, security, medical, industrial control, aerospace and other fields. With the development of modern industry and people's living standards, electronic products are gradually developing in the direction of smaller, lighter and more convenient. The PCB is an important part of the electronic product, due to problems in processing instruments and equipment, during the manufacturing process, there will be burrs, defects, lack of welding and leakage of welding and other defects, resulting in short circuits or overheating, and further can even cause components to burn and explode. Such products manufactured due to PCB defects have a serious impact on the economy or development of companies [1], so defect detection for PCBs is of significant research value.

In this paper, we propose an improved Single Shot MultiBox Detector (SSD) classification system for PCB defect recognition, build its own dataset, use various methods such as flipping, cropping and deformation to expand the dataset with data, and improve the sum accuracy and robustness of the model through Squeeze-and-Excitation Networks(SENet) and Coordinate Attention Mechanisms (CA).

2. Related Work

The majority of PCBs do not function properly in electronic equipment due to defects in the design or manufacturing process. The following five defects often exist in the PCB production process, defined as: kongdong; louhan; lajian; shaoxi; and lianxi, such as Figure 1.

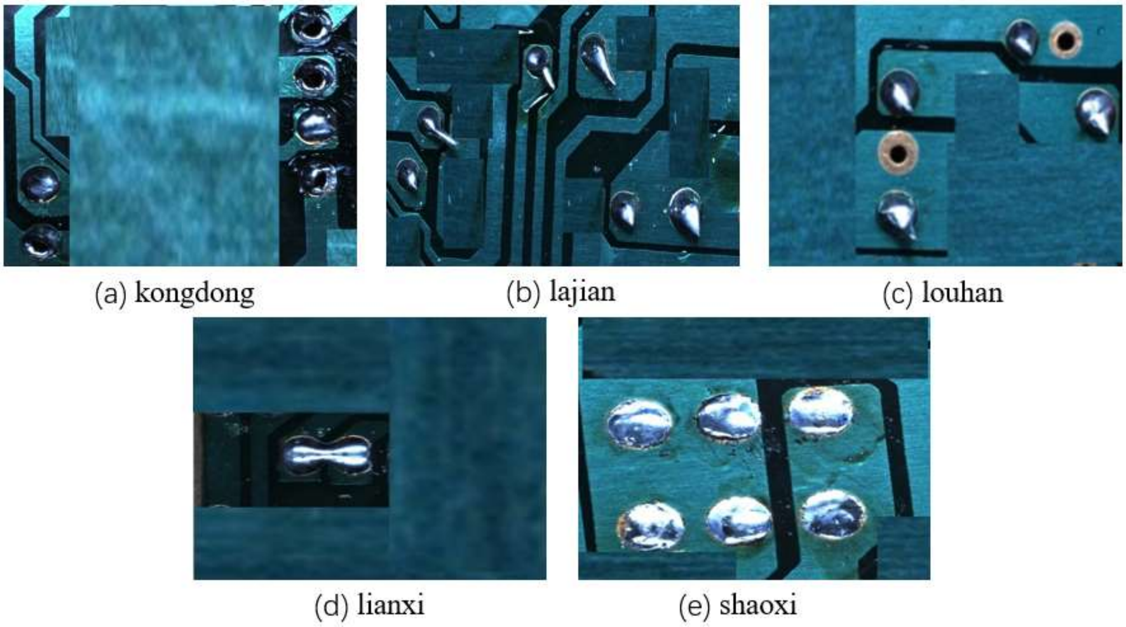

Figure 1. Face Expression Categories

Before machine vision technology was commonly used, traditional PCB defect detection methods included manual visual inspection and electrical testing, where the manual visual inspection method was used to detect defects in PCBs by the quality control workers, which used the naked eye and other auxiliary magnification equipment. As the precision of the PCB is enhanced, the techniques that rely on manual detection methods are prone to errors, omissions, low accuracy, slow detection speed and other problems, while long-term inspection of precision products will cause visual fatigue to the staff on the production line, and even damage their visual health in the long run [2,3]. The electrical test method detects circuit defects in PCB through contact inspection, but the electrical test method requires complex test circuits to be designed for each batch of PCB, and expensive moulds and fixtures also need to be made.

Automatic Optic Inspection (AOI) [4] is an optical inspection with machine vision as the core, through the physical PCB product image acquisition and processing, and ultimately defect detection and quality control. AOI technology is very mature. Although many companies and scholars continue to invest in related research, the AOI technology used for PCB defect detection system equipment is expensive, which is not conducive to the use of small and medium-sized enterprises. And deep learning is just to make up for the traditional PCB testing equipment to detect low, low efficiency, high equipment price.

In the field of deep learning, Hu [5] proposed an improved feature pyramid architecture based on Faster RCNN, which effectively utilizes deep feature extraction networks, but Faster RCNN is slow and has some limitations in practical application species. Tsai [6] proposed a CNN-based model combined with support vector regression (SVR) for the detection of solder leakage, but it is not good to detect other types of defect detection. Wen Li [7] proposed PCB defect detection based on improved YOLO v3. The SENet was added to the network to highlight the useful feature channels in the image data and improve the accuracy of detection. At present, the Faster RCNN represented by accuracy and the YOLO series by speed, which used in target recognition network , cannot take into

 Volume 8 Issue 6, 2022
DOI: 10.6919/ICJE.202206_8(6).0045

account the detection accuracy and detection speed. While the SSD algorithm combines the advantages of both, using a fixed frame for region generation based on the first-order network and utilising multiple layers of feature information to improve the detection speed and detection accuracy of the model, which is suitable for real-time PCB defect detection in real production environments.

3. SSD Defect Detection Network

3.1 SSD Algorithm Network Framework

We have chosen the SSD network as the basic structure, As shown in Figure 2, an end-to-end target detection network, target detection is performed using several feature maps at different scales, where low-level feature maps detect small targets and deep-level feature maps detect large targets. The original SSD network was trained and predicted directly on the constructed dataset, with an mAP of 95.18% and a frame rate of 50fps. However, the SSD algorithm also has the shortcoming of low detection accuracy for small targets. This paper will improve on the original SSD algorithm.

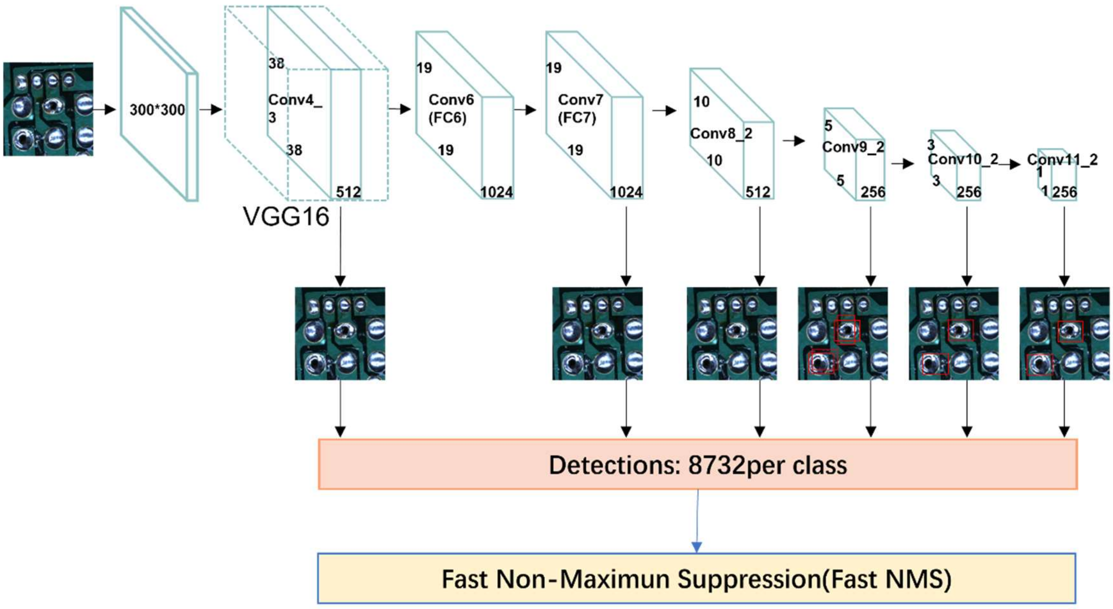

Figure 2. SSD network structure

SSD network is a convolution of a picture divided into different grids. The basic principle is that when the centroid of an object falls in this region, this object is determined by this grid. That is, each grid has a priori frame centered on the center of the grid. These priori frames are pre-marked in the image, and then the prediction results will adjust them to the actual size of input image. Finally, get the prediction result. This is the purpose of segmenting so many grids, and each corresponding grid will correspond to multiple a priori boxes. In this paper, the total number of feature layers is 8732. We adjust 8732 priori boxes, use non-maximum suppression method to find PCB defects that need to be detected, and identify the defect types.

3.2 Attention Modules

Due to the image size of the PCB defect target is relatively small in the data concentration of this paper., the recognition accuracy of the original SSD network model is not enough. So in this paper, we Improve the problem of insufficient recognition accuracy of small targets by using SENet and CA, focusing on the key features of the image, and weakening the weight of the image-independent features.

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3.2.1 SENet

The SENet proposed by Hu [8] is a lightweight channel attention module, which is mainly used to weaken the weight of irrelevant information, assign different weights to the features of different channels, help the network to further focus on key features, explore the relationship between channels, and effectively amplify key information. As shown in Figure 3, the SENet architecture include 5 parts, global average pooling is performed on the input feature layer to get U. Then perform two full connections, the first full connection has a smaller number of neurons, and the second full connection has the same number of neurons as the input feature layer. After that, the value is fixed between 0 and 1 through the sigmoid module,and we obtain the weight of each channel of the input feature layer. Finally, multiply this weight by the original input feature layer, and we get the $\widetilde{X}$, which is the improved result of SENet.

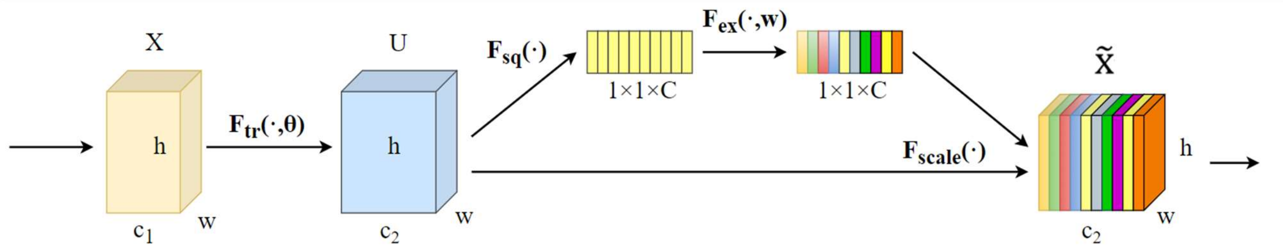

Figure 3. SENet structure

3.2.2 CA

The SENet only assigns different weights to the features of different channels and does not focus on the location information of the features. As a comparison, the CA aggregates features from two directions, horizontal and vertical directions. The coordinate attention, which proposed by HOU Q[9], captures information in one spatial direction while retaining precise location information in another spatial direction, thus better capturing the overall structure of the target and effectively enhancing the representation of salient region features. Its basic principle is shown in Figure 4.

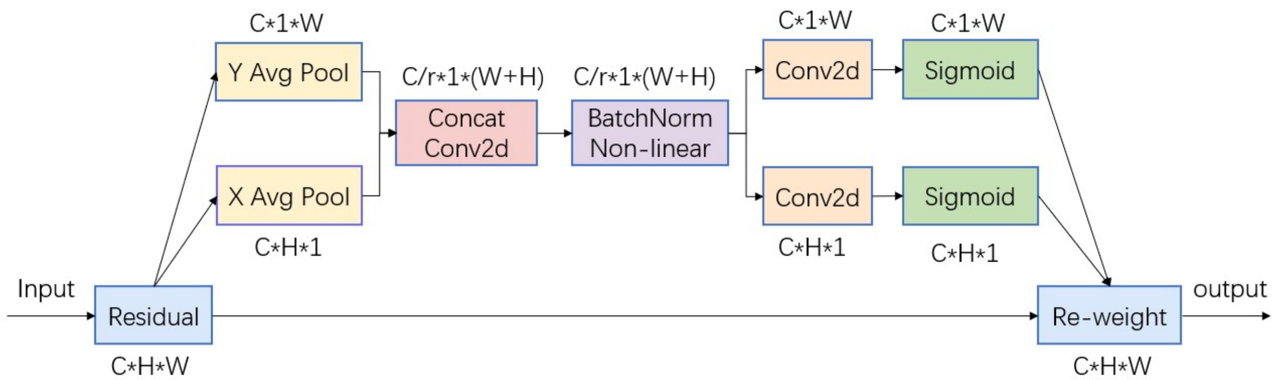

Figure 4. CA structure

It splits the global pooling into two feature encoding operations. Given the input features, two pooling layers are used to encode each channel along horizontal and vertical coordinates, integrating features along two spatial directions and generating a feature map associated with that direction. These two transformations allow CA to better capture the position dependence of the image and contribute to more accurate target localisation. To guarantee that the output has the same magnitude in both directions, a shared convolution layer is used and finally the feature volume is split into two separate tensors along the spatial dimension and the final output is obtained by the sigmoid module.

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3.3 Improved Network Structure

As is shown in Figure 5, the CA had been added behind the backbone network layers Conv4_3, FC7 and Conv8_2 , so that the shallow feature extraction network can accurately predict small objects. Since SDD performs well for large objects, the deep feature extraction network remains unchanged. Finally, through non-maximum suppression, the redundant bounding boxes are filtered out, and the detection result is generated.

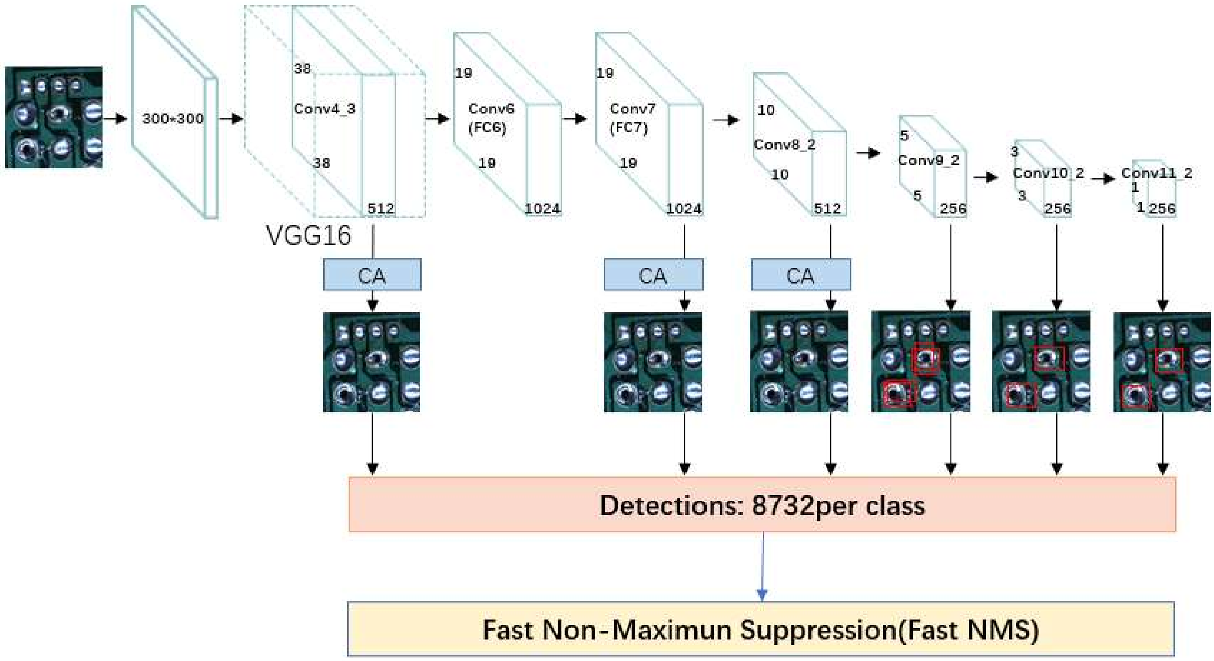

Figure 5. Improved SSD structure

4. Experiments

4.1 Datasets

This paper uses a dataset collected by myself. The dataset in this paper is based on common types of PCB defects, with five defect categories soldered separately. The dataset images were taken using the same lighting method, the same light intensity and a fixed perspective. Due to the small number of the original dataset, this paper uses a variety of means to expand the dataset such as image flipping, mirroring, panning, etc. The distribution of the types and numbers of the final dataset is shown in Table 1, which specifically includes five categories of kongdong, louhan, lajian, shaoxi and lianxi. The PCBs were annotated using the labelImg tool to survive xml annotation files, and these datasets were divided into training, validation and test sets according to 8:1:1.

Table 1. Dataset

Category	Kongdong	Louhan	Lajian	Shaoxi	Lianxi
Samples	402	402	402	402	402

4.2 Experimental Environment

The software environment for this paper is Python 3.7 and Pytorch 1.11.1 deep learning network, the GPU hardware parameters are GeForce RTX 3050 Laptop, and the running memory is 4GB.

In this paper, we set the hyperparameters based on the pre-trained SSD algorithm weights, the batch size was set to 8, the weight decay coefficient was 0.0005, the learning rate was set to 0.0001, and the epoch is set to 100.

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4.3 Experimental Result

In order to verify whether the addition of CA really improves the accuracy of SSD for PCB defect detection, this paper compares the improved SSD model with the original SSD model for PCB defect detection through different experiments. Table 2 shows the performance metrics of the improved detection of each defect, as well as a comparison with other algorithmic models, and the effectiveness of the various models for PCB defect identification is shown in Table 3.

Table 2. Performance indicators for detection defects

Networks	AP (%)	Recall rate(%)	Precision (%)	F1(%)
SSD + CA(louhan)	93.52	81.31	90.16	86
SSD + CA(shaoxi)	99.96	97.53	99.99	99
SSD + CA(lajian)	93.96	68.75	94.29	80
SSD + CA(lianxi)	97.89	92.74	96.64	95
SSD + CA(kongdong)	96.96	87.64	91.76	90

Table 3. Result of Comparative Experiment

Networks	mAP (%)	Recall rate (%)	F1(%)	Frame rate (fps)	Size (KB)
SSD	95.18	81.69	86.6	50	94,871
YOLOv3	88.71	81.27	85.6	32	240,735
SSD + SE	95.78	85.56	89.4	50	94,871
SSD + CA	96.46	85.59	90.0	50	94,871

As can be seen from Table 3, the original SSD is superior than YOLOv3 in mAP metrics ,frame rate and the model size. after optimisation with CA, the model size remains the same.The improved model achieved the best performance among all the reference models in all metrics. As shown in Figure 6, the improved model can quickly and accurately identify the different defect categories in (a) - (f).

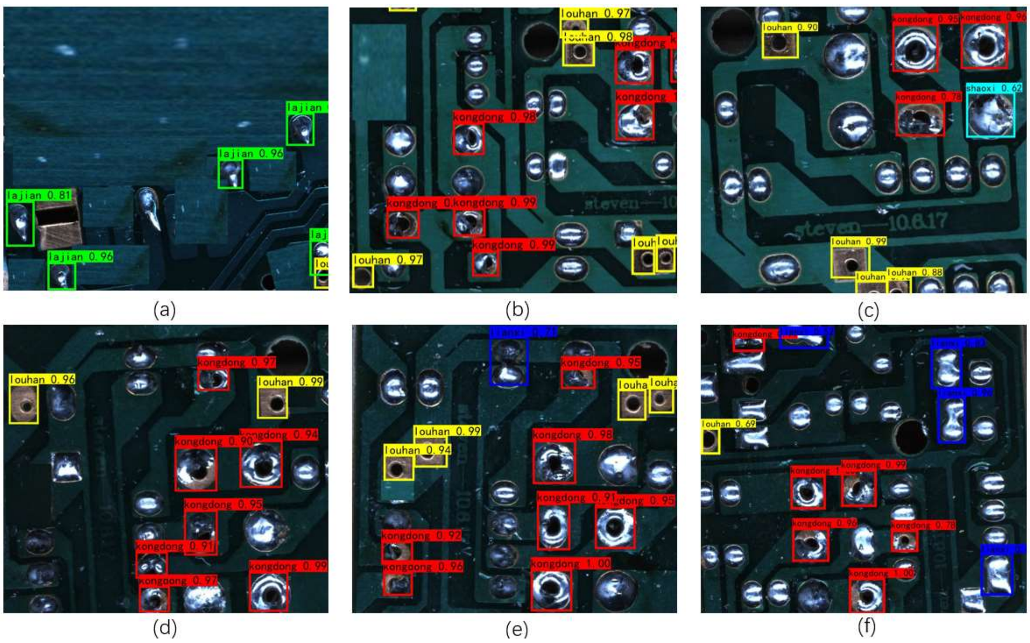

Figure 6. Practical testing of the improved SSD network

5. Conclusion

In this paper, we use the deep learning framework Pytorch to propose a PCB defect detection model with added attention mechanism based on SSD network to achieve intelligent detection of PCB defects as well as real-time detection. Experiments show that both the added SENet and CA can improve the accuracy of the algorithm, and the recognition accuracy of the SSD network with the addition of CA will be higher. The model accuracy and speed of this paper is significantly better than the traditional SSD network, and the comparison with the YOLOv3 network is also with the advantages of model accuracy and speed as well as large model. The improved SSD network in this paper does not require high hardware configuration of the experimental equipment and can meet the target detection requirements in practical applications.

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