A DEFECT DETECTION SYSTEM FOR PCB MANUFACTURING SYSTEM BY APPLYING THE YOLOV4 ALGORITHM

NGHIÊN CỨU THIẾT KẾ HỆ THỐNG KIỂM TRA LINH KIỆN ĐIỆN TỬ CHO SẢN XUẤT BẢN MẠCH IN PCB ỨNG DỤNG YOLOV4

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ABSTRACT

Defect detection is recognized to be the most integral criterion for the printed circuit boards (PCBs) quality in industrial manufacturing. The traditional PCB inspection methods have several disadvantages such as time-consuming, labor-intensive, environmental clutter - susceptibility, and inaccurate detection ability. This paper offers a deep learning method for PCB defect detection. This method builds an improved neuron network based on the YOLOv4 algorithm. A CSPDarknet53 is used with feature pyramid networks as the backbone for feature extraction. Secondly, the spatial pyramid pooling layer and the path aggregation network are utilized to predict better mimic errors on the PCB components. Finally, the experimental results indicate a more reliable and efficient performance compared to the existing works.

Keywords: *PCB, automated optical inspection (AOI), YOLOv4, defect detection, convolutional neural networks.*

TÓM TẮT

Hệ thống kiểm tra linh kiện điện tử là thành phần bắt buộc trong các dây chuyền kiểm soát chất lượng khi sản xuất bản mạch in PCB. Các phương pháp kiểm tra PCB truyền thống có một số nhược điểm như thời gian tính toán, nhiều nhân công, dễ bị tác động bởi môi trường làm việc, và độ chính xác không đảm bảo. Bài báo này đề xuất phương pháp kiểm tra linh kiện điện tử sử dụng giải thuật học sâu dựa trên mạng nơron cải tiến YOLOv4. Trong đó, CSPDarknet53 được sử dụng để trích xuất các đặc trưng cho hệ thống nhận diện linh kiện điện tử. Kết quả thực nghiệm cho thấy hiệu suất đáng tin cậy và hiệu quả so với các công trình công bố gần đây.

Từ khoá: *PCB, hệ thống kiểm tra ngoại quan tự động, YOLOv4, phát hiện khuyết tật, mạng nơ-ron tích chập.*

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Received: 15/8/2021
Revised: 30/9/2021
Accepted: 15/11/2021

1. INTRODUCTION

Printed circuit board (PCB) [1 - 3] makes up the main components of electronic products in the market. PCB defects are one of the critical factors for a high defect rate of electronic equipment. Therefore, defect detection is an important quality control technique for the PCBs industry. Different PCB defects [4 - 5] can be generated in various production processes, such as missing values, lacking components, mistaken open circuits, and short circuits, causing the yield to drop. Therefore, it is necessary to achieve non-contact, accurate, and efficient automatic defect detection in the PCBs production process.

With the development of technology, various methodologies based on computational intelligence have been proposed to solve the problems of electronic surfaces in non-periodical pattern images [6 - 13]. The template matching is one of the feasible techniques to apply, where a defect-free sample image (or a set of defect-free images) is used as the template to compare the deviation with the test image pixel by pixel. Chua et al. [14] applied the golden template method for bond pad defect detection in the wafer. The widely used template matching methods for industrial inspection applications are either the image difference by sum of absolute difference and mean squared error [15] to meet the real-time inspection requirement. These approaches can successfully detect large-sized defects. Since these features rely on hand-crafted features, there are two pitfalls: (a) It might not be possible to describe complex image scenes and object structure. (b) The adaptability to new views and the generalization ability is reduced.

The automated optical inspection (AOI) technique based on machine vision also has been utilized to detect the defect during the PCB manufacturing process [16]. Compared with traditional manual detection, it has a series of advantages such as high-speed detection, cost reduction, and accuracy. In this defect detection method, the correlation between the scene images and the two window portions of the reference image is calculated. Nevertheless, the difficulty of this method is the precise alignment of the reference image and the testing image. Performing the alignment operation requires a complicated configuration process. At the same time, the detection process is susceptible to light and noise, and even small shadows can cause false alarms. R. Ding et al. [17] proposed an approach is based on Faster-RCNN to detect tiny defects of PCB and achieved high precision. This method solves the shortcomings of deep convolutional networks in detecting small defect areas, obtains good experimental results on an open PCB defect database. Some researchers have used the method based on Faster-RCNN [18, 19] in defect detection and achieved excellent results. However, in the case of complicated scenarios, these approaches are sensitive to noise, illumination, and shift changes.

In this paper, a real-time PCB inspection system is proposed for normal cameras under the circumstances of high influence from complicated environments. The you only look once (YOLO) algorithm is a superior object detection technique [20 - 23]. The proposed method is designed based on the YOLOv4 network [25]. This paper calls sheds remarkable light on this fields as follows:

(1) By adding some improved training strategies, the mini-batch size has almost no effect on the detector's performance. This result shows that it is no longer necessary to use expensive GPUs for training.

(2) The designed system generates a small amount of data to be operated; therefore, this could be simply done in real-time.

(3) The proposed approach is applied and evaluated on the PCB inspection system.

The rest of the paper is organized as follows. The next section analyses the detailed structure of the proposed approach. In section 3, the overall characteristics of the designed system are expressed. Section 4 summarizes the experiment platform and its result, followed by the brief conclusions in section 5.

2. THE PROPOSED METHODOLOGY

This section is divided into two subsections. The first subsection gives a brief overview of the proposed YOLOv4 model. In the next subsection, the loss function of the proposed method is analyzed.

2.1. The YOLOv4 detection model

This paper offers the YOLOv4 detection model which is composed of several parts as shown in Figure 1. The YOLOv4 algorithm employs convolutional neural networks (CNN) [29, 30] to detect objects in real-time. This means that prediction in the entire image is done in a combined algorithm run. After pre-training to predict various class probabilities and bounding boxes simultaneously, the YOLOv4 model is used to classify different types of components on the PCB surface. The structure of the YOLOv4 model is illustrated as follows:

- Input: Image, Patches, Image Pyramid
- The backbone and the neck: In the backbone, CSPDarknet53 [25] is applied, while the spatial pyramid pooling layer (SPP) [26], the path aggregation networks (PAN) [27] are taken as the neck of the proposed network.
- The heads include the dense prediction at the first stage and the sparse prediction at the second stage. To be more specific, we use the YOLOv3 [28] to build the head layers of the proposed network.

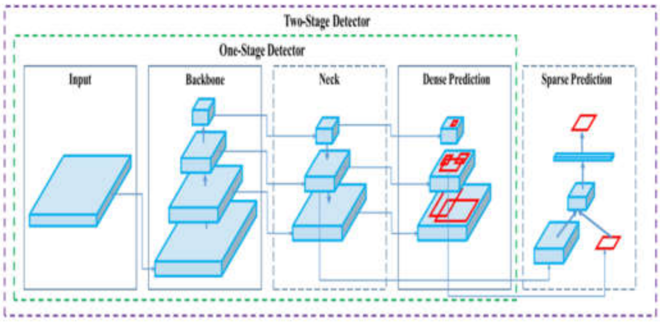

Figure 1. The structure of the YOLOv4 detection model [25]

2.2. The Loss Function of YOLOv4

The loss function L_{loss} [31] of the YOLOv4 training model included the bounding box location loss (λ_{CIoU}), the confidence loss ($\lambda_{confidence}$), and the classification loss (λ_{Class}). In general, the loss function is calculated as:

$$L_{loss} = \lambda_{CIoU} + \lambda_{confidence} + \lambda_{Class} \quad (1)$$

To be more detailed, the bounding box location loss is expressed as:

$$\lambda_{CIoU} = 1 - IoU + \frac{d^2}{c^2} + \sigma v \quad (2)$$

The confidence loss is designed as follows:

$$\lambda_{confidence} = \sum_{i=0}^{S^2}\sum_{j=0}^{B} K[-\log(p) + BCE(\hat{n}, n)] \quad (3)$$

The classification loss is designed as

$$\lambda_{confidence} = \sum_{i=0}^{S^2}\sum_{j=0}^{B} 1_{i,j}^{noobj}[-\log(1-p_c)] \quad (4)$$

Where as:

$$BCE(\hat{n}, n) = -\hat{n}\log(n) - (1-\hat{n})\log(1-\hat{n}) \quad (5)$$

$$\sigma = \frac{v}{(1-IoU)+v} \quad (6)$$

$$v = \frac{4}{\pi^2}(\arctan\frac{w^{gt}}{h^{gt}} - \arctan\frac{w}{h})^2 \quad (7)$$

$$K = 1_{i,j}^{obj} \quad (8)$$

IoU represents the ratio of the intersection and union of the predicted bounding box and the ground truth bounding box, while c and d are the distance between the centers of the two bounding boxes and the diagonal distance of their union respectively. w^{gt} and h^{gt} are the width and height of the ground truth bounding box, while w and h represent the width and height of the predicted bounding box. S is the number of grids, and B is the anchor number corresponding to each grid. K represents weight, and its value is one if there is an object in the j^{th} anchor of the i^{th} grid, otherwise, it is zero, while and n represent the actual and predicted classes of the j^{th} anchor in the i^{th} grid, respectively, and p is the probability that the object is components of the PCB.

3. THE PCB SUPERVISION SYSTEM

3.1. Calibration of the camera position

To ensure the precision of the input images, we calculate the position of the camera based on the camera operation zone and the size of the real PCBs.

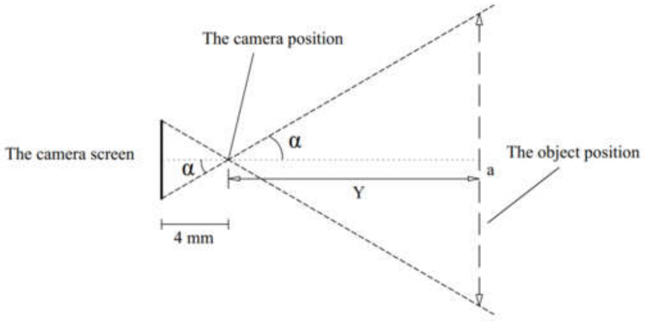

Figure 2. The camera position calibration

The distance between the screen and the sensors is focal of the camera lens. The shorter focal leads to the larger camera operation zone. Hence, we set up the camera at the position which is perpendicular to the plane containing the object. Moreover, the distance Y from the position of the camera to this place is expressed as follows:

$$Y = \frac{1}{2} a \cot \alpha \tag{9}$$

3.2. Design the PCB automated inspection system

For the purpose of revising the PCB image processing, we propose the PCB automated inspection as in Figure 3.

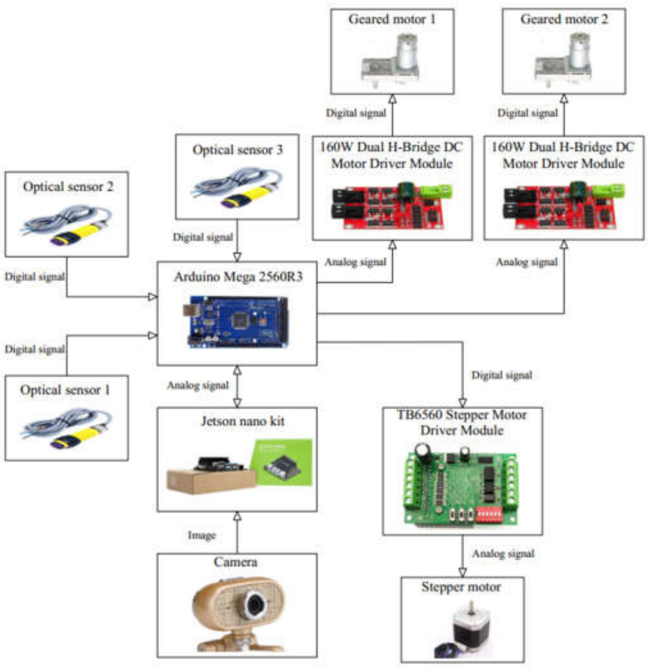

Figure 3. The PCB automated inspection

4. EXPERIMENTAL RESULTS

To verify the robustness of the proposed approach, our designed system is applied to a real PCB defect database. The database contains 200 PCB images that have been correctly labeled. These PCB images are normally divided into five types of defects (missing hole, blur color, open circuit, mimic cracked, and spurious copper). It could be seen that the performance of the model is affected by environmental elements such as brightness, background, and image resolution. Besides, the precision percentages of the proposed model are compared to those of the YOLOv3 method [28].

4.1. The influence of the brightness

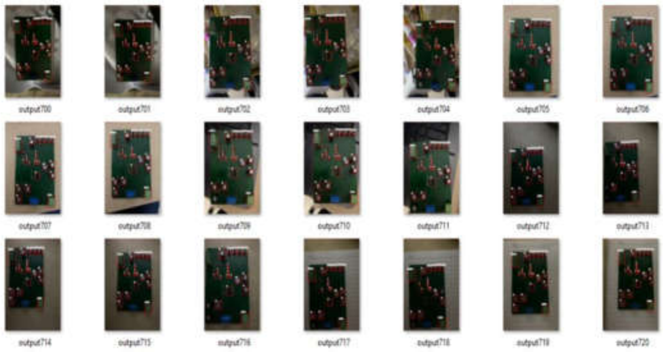

Figure 4. The influence of the brightness on the proposed model

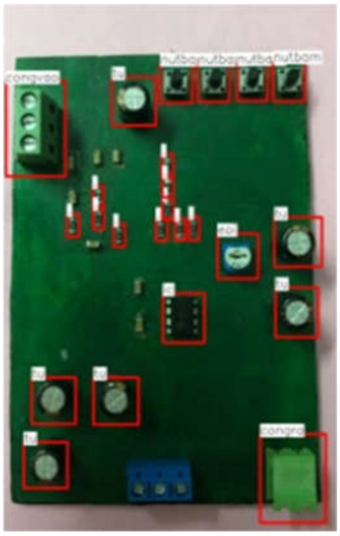

Figure 5. The PCB components inspection in case of good condition light

Figure 6. The comparisons between YOLOv3 and YOLOv4 algorithm among different condition light

Figure 4 - 5 shows the detection images of the proposed approach, whereas Figure 6 indicates the comparisons between the YOLOv4 and YOLOv3. Broadly speaking, the two mentioned methods work well in good

condition light. However, the single most observation to emerge from the data comparison in case of poor condition light. To be more detailed, the successful detection images of the YOLOv3 are only 102 images (51%), while the figure for the YOLOv4 is significantly higher - at about 124 images (62%).

4.2. The influence of the backgrounds

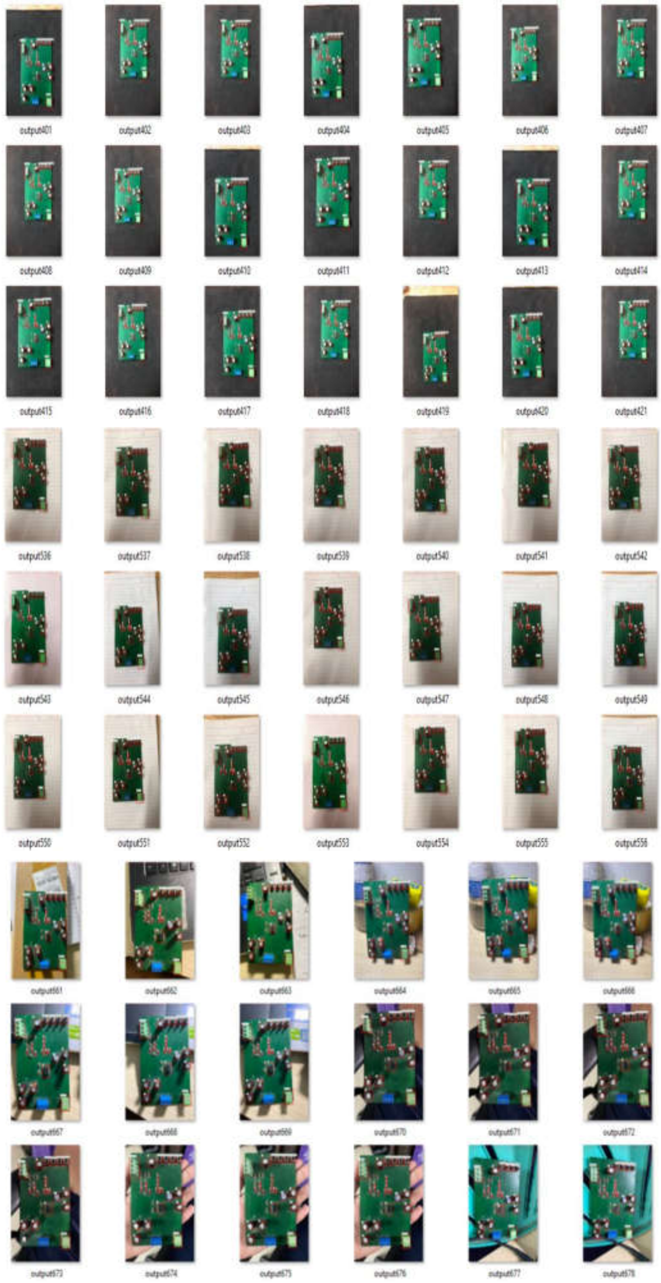

Figure 7 . The influence of the backgrounds to the proposed model

To figure out the background influence, we conduct the experiments based on the complexity of the environmental color. The results as shown in Figure 7-8 reveal that there is no significant disparity in the precision rate between the two mentioned methods. Nonetheless, the most surprising is with the GPU time processing. Among different scenarios, the YOLOv4 GPU time is rapidly faster compared to the YOLOv3 method. For instance, in the case of the random background, the YOLOv4 just needs 1.4 s/PCB to finish the detection process. In contrast, the speed of the YOLOv3 method is slower, at nearly 2.2 s/PCB.

Figure 8. The comparisons between YOLOv3 and YOLOv4 algorithm in case of different backgrounds

4.3. The influence of the image resolution

We use calibration experiments to evaluate the merits of the YOLOv4 network proposed in this article. The image dataset is scaled into different resolutions to revise that using YOLOv4 can still maintain high-precision detection compared to the YOLOv3 method. Figure 9 shows the calibration experiment results.

Figure 9 . The influence of the backgrounds to the proposed model

Table 1. The influence of the image resolution

Resolution	YOLOv4 network		YOLOv3 network	
	Passed images	Failed images	Passed images	Failed images
1512x2016	171	29	162	38
960x1280	194	6	192	8
480x640	195	5	190	10

From Table 1, it is fundamental to note that the YOLOv4 network has better accuracy in detecting defects than the YOLOv3. Moreover, the accuracy of the error-types detection has been improved significantly. It can reduce 20% environmental cluttering then the YOLOv3 and generate more accurate proposals.

5. CONCLUSION

In this novel, a PCB manufacturing system based on the YOLOv4 network is presented to ensure the good performance of the inspection process. The proposed approach can not only work effectively among different types of defects but also requires little computational effort. Moreover, by applying the CSPDarknet53 backbone into the network, the feature extraction is improved more precisely. Finally, the SPP technique is changed compared to the YOLOv3. It is no longer about dividing feature maps into bins and then concatenating these bins together to get a fixed-dimensional vector. Hence, the designed network is robust against noise and the detection process is speed up significantly. In conclusion, the paper points out the advantages of the PCB manufacturing system based on the YOLOv4 algorithm. The experimental results have indicated the feasibility and effectiveness of the proposed method.

ACKNOWLEDGMENT

The authors would like to send sincere thanks to the Hanoi University of Industry for their financial support in the implementation of this study.

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