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# Using Deep Learning to Automatic Inspection System of Printed Circuit Board in Manufacturing Industry under the Internet of Things

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**Abstract.** Industry 4.0 is currently the goal of many factories, promoting manufacturing factories and sustainable operation. Automated Optical Inspection (AOI) is a part of automation. Products in the production line are usually inspected visually by operators. Due to human fatigue and inconsistent standards, product inspections still have defects. In this study, the sample component assembly printed circuit board (PCB), PCB provided by the company was tested for surface components. The types of defects on the surface of the PCB include missing parts, multiple parts, and wrong parts. At present, the company is still using visual inspection by operators, the PCB surface components are more complex. In order to reduce labor costs and save the development time required for different printed circuit boards. In the proposed method, we use digital image processing, positioning correction algorithm, and deep learning YOLO for identification, and use 450 images and 10500 components of the PCB samples. The result and contribution of this paper shows the total image recognition rate is 92% and the total component recognition rate reaches 99%, and they are effective. It could use on PCB for different light, different color backplanes, and different material numbers, and the detection compatibility reaches 98%.

**Keywords:** Deep learning, Digital image processing, Printed Circuit Board (PCB), Automatic inspection system.

## 1. Introduction

Under the rapid development of industry 4.0, automatic factory began to be implemented in major factories. Robots will replace operators. In the future, robots are more likely to be used in the service industry and even appear at home to help people live a better life. The products produced in the factory will require a lot of manpower to check and remove defective products. The problem scenario is printed circuit board (PCB) proposed in this research has extremely small and complex components. Due to the fatigue of the operator’s visual inspection, the quality of the product gate will be affected to a certain extent after a long time of work, even due to people. Different standards are different, automated inspection systems will be used to solve many of these problems, make product inspections more consistent and more efficiently, and can operate for a long time, which will replace the entire operating system and bring greater benefits [16, 26, 27].

The commonly used equipment for printed circuit board inspection is In-Circuit-Test (ICT) and Function Verification Test (FVT). The functions that the PCB inspection machine can detect are open circuit, short circuit, faulty parts, missing parts, measuring resistance. Measuring capacitance, measuring diodes, and measuring various electronic parts, some of which use Automatic X-ray Inspection (AXI) to penetrate and inspect the internal quality. At present, Automated Optical Inspection (AOI) has been widely used on PCB, such as missing parts, skewed, standing parts, wrong parts, pin warped, short circuit, solder ball detection. Due to the high price of commercially available printed circuit board inspection machines, the use of Automated Optical Inspection (AOI) can reduce the additional purchase cost of the inspection machine, but it still be due to the different products of the PCB, and the algorithms behind it will also be followed. Change the detection compatibility is low, and often cannot be used on the next product. Therefore, this paper will use image processing, positioning point correction and deep learning to develop a detection system for the components on the PCB [1, 11].

At present, PCB surface defects are inspected visually by operators. Fatigue and personal factors will affect the product yield. The purpose of this research is to solve the problem of PCB inspection inconsistency and long-term operator fatigue. The advantages of the proposed method to develop a detection system for parts and faulty parts, and finally test whether the detection system can be used efficiently on other PCB with different light, different background colors, and different material numbers to verify the compatibility of the detection to reduce equipment purchase and the issue of labor costs [31, 34].

In this study, PCB-related products provided by cooperating manufacturers are used as experimental samples, and the field of view (FOV) size of 24mm x 24mm is tested. Since the development of automated testing systems requires the use of many hardware devices, with optical environment architecture, and no ambient light is strong, this experiment uses image processing and deep learning, and the system parameters are learned through experiments. The conditions are as follows: use a 2/3-inch photosensitive chip, a 8 million pixel industrial color camera, and a CCTV lens with a focal length of 45mm and a 5mm extension ring. Use RGBW four-color bowl-shaped light source with a diameter of 250mm. The captured image format is limited to 2048*2048 pixels bitmap images, using universal robot, using conveyor belt with a width of 450mm. The contribution of this paper shows the total image recognition rate is 92% and the total component recognition rate reaches 99%, and they are effective. It could use on PCB for different light, different color backplanes, and different material numbers, and the detection compatibility reaches 98% [33, 39].

This paper's organization includes in section 1. Include paper background, motivation and purposed. Section 2 literature review will learn about digital image processing (DIP) and deep learning applications. The section 3 research method and experimentation. Section 4 is the results and data of the experiment discussion. Section 5 is the conclusion include contribution, future work and limitation.

## 2. Literature Review

This research mainly focuses on the provided PCB samples after component assembly, detecting surface component defects, and using robotic arms to assist in the work.

### 2.1. PCB component inspection

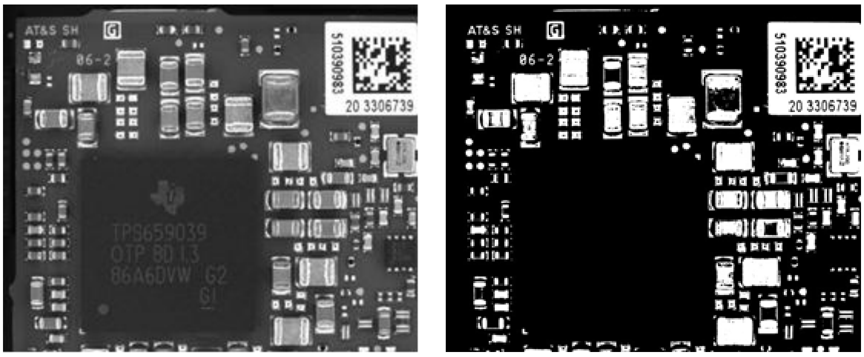
PCB testing mainly includes internal testing and appearance testing. Internal testing is mainly based on testing machines, including ICT or FVT and other equipment, the main content is to detect whether the circuit has an open circuit, short circuit, and the measurement of many electronic components. Appearance inspection usually uses AOI, which requires opto-mechanical equipment and image processing algorithms. The main inspection contents are surface scratches, missing parts, excessive tin, and foot deformations. Solder ball inspection can use opto-mechanical equipment to produce suitable solder ball feature images, and detect defects such as tin tip and excessive tin. Recent literature also uses three-dimensional measurement methods to establish its three-dimensional map to detect its complete three-dimensional appearance [4, 12]. At present, there are quite a lot of papers on PCB component detection, most of which are detection using image processing techniques, including image subtraction, component matching [25]. In recent years, the use of machine learning and deep learning has made great contributions to image recognition [9]. Many types of defects have been detected by deep learning. This study intends to use deep learning to detect missing parts, multiple parts, and wrong parts in PCB. Therefore, several articles related to the use of deep learning in PCB component inspection. VGG-16 has the best results, with better accuracy, and can identify up to 25 different components. R-CNN performs positioning, and the mAP is good. RCNN to detect tin on printed circuit boards, the types of defects detected include tin bridges, double tin balls, empty tin. YOLO to detect 9 kinds of capacitors, all of which can be detected. The average time is less than 0.3 seconds. Faster RCNN to identify the components on the PCB and verified that this method is better than template matching. A histogram as the input of a neural network to identify component memory, its method has better success rate. Using neural network to detect whether the solder feet are defective, and finally detect the verification rate is better too.

A fast defect detection network used k-means clustering algorithm is used to obtain more reasonable anchors boxes; second, an improved MobileNetV2 is used as the backbone network; after the feature extraction network, the spatial pyramid pooling (SPP) structure is introduced to increase the receptive field of the image [17]. PCB defect detection by using machine learning and other approaches. The current research shows that PCB defect detection using machine learning are miniscule. Early detection is still unexplored and experimented in the industry [40].

### 2.2. Digital image processing

Digital image processing is a method of image processing. Its concepts include scraping filtering, capturing, segmentation. A publicly available dataset, FICS-PCB, to facilitate the development of robust methods for PCB-AVI. It has three variable aspects: illumination, image scale, and image sensor [23, 24]. The following will list the calculation logic that will be used in PCB inspection, and refer to Digital Image Processing book content and other literature exploration.

Threshold: Binarization is a common technique in image processing. It can also be said to be a dichotomy. It is often used for grayscale image segmentation to change the color to only pure black and pure white. It can also be used for every color image. Its main purpose is to reduce noise and form a black or white image with strong color contrast to facilitate subsequent morphological processing or feature interception [17-21]. Binarization must be given a threshold. When the input is less than this threshold, its value is 0 (black), otherwise it is 255 (white) as Fig. 1.




(a) Original image (b) Binarized result

**Fig. 1.** Principle of Binarization (Cheong, 2019)

Contour detection is to find the outer contour of an original image after binarization and morphology. For automatic detection, it can detect the pixel size of the defect and determine whether there is a defect beyond the specified range. Other applications of contour detection can find the outermost contour of the target, and know the degree of contour skew. On the one hand, it can detect whether the PCB component is skewed or offset, and on the other hand, it can obtain its coordinates, which can be repositioned and corrected to be measured. This method is usually used for image subtraction. First, find two points that are more accurate and have little variability, and connect these two points to form a vector, and then use this vector to translate and rotate the image to correct it [5, 13, 37, 38, 45].

Image subtraction is a very practical technique. It is a subtraction of two images taken at different points in the same environment, the same camera and the same light source. This technique is more commonly used in three scenarios. One is to solve the problem of light and shadow. Each image usually has uneven light and shadow. The threshold of binarization is difficult to preset. If you first take a background image, when the image of the object is subtracted from the background image, a more uniform effect can be achieved. The second is to find a moving target. In the case of continuous orientation, this image is subtracted from the previous image to obtain the trajectory of the moving object, and contour detection is used to frame it to obtain the moving target. The third method is used to detect defects [2, 24, 30, 44]. The method is the same as the first method. The difference is that first take a standard image of the product without defects, and correct the positioning. When the image of the object to be tested is taken, it is compared with the standard image. By subtracting the image, the defect can be obtained, which can be used for defects such as missing parts of the PCB, severely distorted parts, and short circuits on the circuit.

### 2.3. Deep Learning Applications

With the advancement of neural networks, it can help automated inspections to identify defects more effectively. Back Propagation Network (BPN) [14] and even Convolutional Neural Networks (CNN), CNN is a major breakthrough. Almost all networks are based on CNN to improve and develop. The detection network used in this research, YOLO (You Only Look Once) is also developed based on CNN [29].

Convolutional Neural Networks: In the original machine learning, the image needs to be flattened into one-dimensional information and then calculated, but this method will lose the original image characteristics, and the convolutional neural network Road is identified by using high-dimensional feature information in the image. For example, humans see birds because they see the beak or the back of the chair. The convolutional neural network architecture includes: Convolutional layer: Given one or more filters, extract each feature in the image according to its size, and get feature map. Pooling layer: Retains the important information left after the convolutional layer. Its advantages are reduce parameters to speed up calculations. If there is a slight change between adjacent pixels, it will have little effect on the output result of the pooling layer and reduce overfitting. Fully connected layer: The flatten the remaining features, performs common neural network operations, and classifies them. CNN goes through a multi-layer convolutional layer and a pooling layer. The convolutional layer is responsible for extracting image features, and then leaving important information after the pooling layer [16]. Finally, the fully connected layer performs the final calculation and classification. The proposed convolutional neural network architecture uses high-dimensional feature extraction and has good recognition capabilities.

YOLO: Image recognition has been widely used similar to neural networks, but CNN can only take one image as input and one output at a time. There is no way to recognize multiple items at the same time, while You Only Look Once (YOLO) can recognize multiple objects at once. This study uses YOLOv3. YOLOv1 was proposed by Joseph Redmon [28, 35], and Fig. 2 is the network architecture diagram. Output an image with an input size of 448x448 as SxS grids (grid; the default is 7x7), and then detect whether there is an object in each grid separately, and generate B (default is 2) bounding boxes and N (default is 20) category of conditional class probabilities, the five prediction parameters in bounding boxes are x, y, w, h and confidence scores, x and y are the coordinates of the bounding boxes, w and h are the width and height of the bounding boxes, confidence scores is the value of whether there is an object 0 or 1, conditional class probabilities is the probability of N categories, and finally the bounding boxes with the object are left, and then use Non-Maximum Suppression (NMS) to select the most suitable frame.

The improvement content of YOLOv2 is to add anchor boxes, the output scale is 13x13 and each grid has 5 anchor boxes to predict bounding boxes, so the maximum output bounding boxes is 845, and the image input size is not limited to 448x448, but a multiple of 32 is the basic structure to change from the original GoogleNet to VGG-16, and Batch Normalization is added to prevent over-fitting and multi-scale training to improve the detection effect. The improvement content of YOLOv3 is to change the output scale to 13x13, 26x26, 52x52, and each grid has 3 anchor boxes to predict bounding boxes. The Feature Pyramid Networks multi-level prediction architecture improves the detection ability of small objects. The maximum number of output bounding boxes is 3549, the loss function is changed from the original sum-squared error to binary cross-entropy, the output activation function is changed from the original softmax to logistic, and the basic architecture is changed from the original VGG-16 to ResNet.

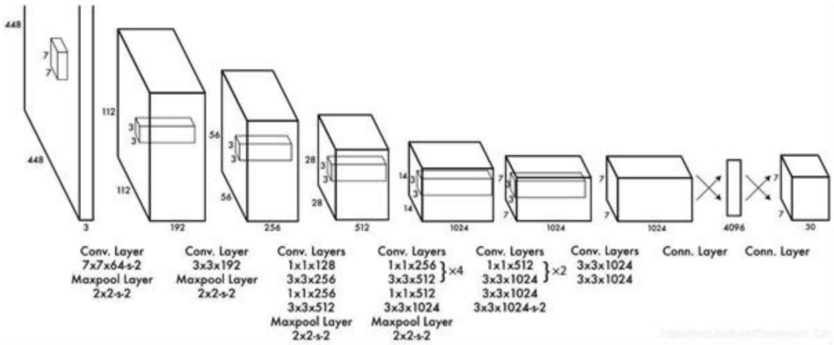



**Fig. 2.** YOLO network architecture diagram (Ki, 2017)

## 3. Research Methods

To sorts out the PCB detection methods belonging to the sample, uses robotic arms to work together, constructs a flowchart to describe the steps, to complete the automated detection system, and test whether this system can be effectively used on other PCBs.

### 3.1. Process of Automated Testing System

The automated inspection system is divided into two steps. The first step is the communication between the image capture operation and the hardware, and the second step is the image post-processing, it is the software inspection. PCB input, the personnel will place several PCBs in the fixture and place the fixture on the conveyor belt. When the sensor knows that the fixture has reached the inspectable range, stop the conveyor belt operation, use the video camera to locate the fixture position, and return it. The coordinates are captured by a robotic arm equipped with an industrial camera and light source. Since the PCB parts are extremely small, this capturing operation will divide a piece of PCB into ten small images.

Fig. 3 is the flow chart of the PCB inspection system. After the image is input, the first operation is performed by the digital image processing (DIP), and then the processed image is input to YOLO, and the components in the image are picked out, and then the components and the original image are transferred to calibration and positioning component algorithm, finally draw the frame on the original image and establish the component coordinates, and determine whether all components have been picked out [6-8, 22, 32, 42]. If one or more components are not picked out, it will be regarded as a defect, and the defective PCB will be rejected. And keep this detection image to facilitate verification whether it is a misjudgment.

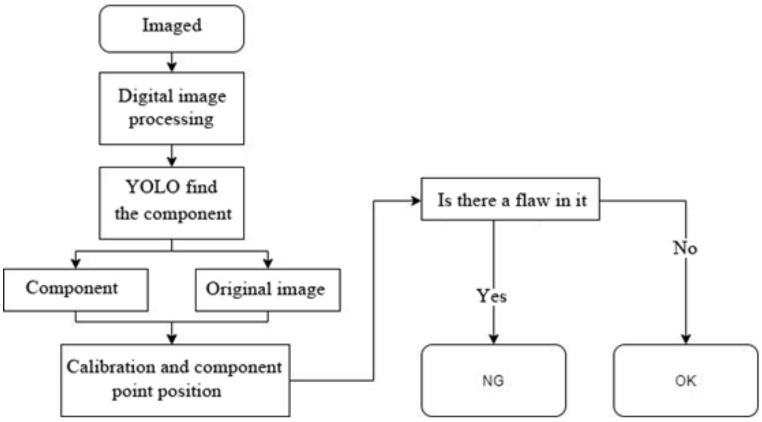



**Fig. 3.** Flow chart of the PCB inspection system

### 3.2. Hardware Architecture Framework and Process

The sample PCB size is 59mm x 50mm. The sensor detects the fixture, sends a signal to stop the conveyor belt, and returns a message. The Input/Output is controlled by Arduino. The lower left is Arduino, the upper left component is an infrared sensor, and the lower right component is a relay for circuit switching. When the sensor detects the fixture, the relay turns off the power supply of the conveyor belt. The coordinate position of the entire fixture is located by the video camera above the mechanism and sent back to the robotic arm. The robotic arm moves to the position of each PCB, and then follows the upper left, upper, upper right, left middle, middle, right middle, lower left, bottom, and right take the next image, and finally take another one on the largest chip. Each PCB has a total of 10 images, a fixture has a total of 10 PCBs, and a total of 100 images per fixture. This research has been cross-validated, using industrial camera with 45mm CCTV lens, and with past experience, using HZTEST's AOI-220-RGBW four-angle four-color bowl light source, The characteristics of the solder ball can be effectively shot to facilitate future inspections.

### 3.3. Detection Architecture

The detection architecture is divided into two phases, the first phase is the model training phase, and the second phase is the detection component phase. The detection component stage is subdivided into three stages. The first stage is image pre-processing, the second stage uses model detection components, and the third stage data post-processing and output. This experiment will build software to implement digital image processing with the python library provided by OpenCV, and use Keras, Tensorflow.

This research uses YOLO to pick out the components. Label each component, use YOLO to train its samples, and predict each component, thereby knowing the location of each component. The model training stage is subdivided into two stages. The first stage is to number the components, and the second stage is to divide the components into a total number of methods and models. In the first stage, the components are numbered. In this experiment, the components on the PCB board are divided into 11 types, which are A, B, C, D, E,...,K according to the size of the components, as shown in Fig. 4.

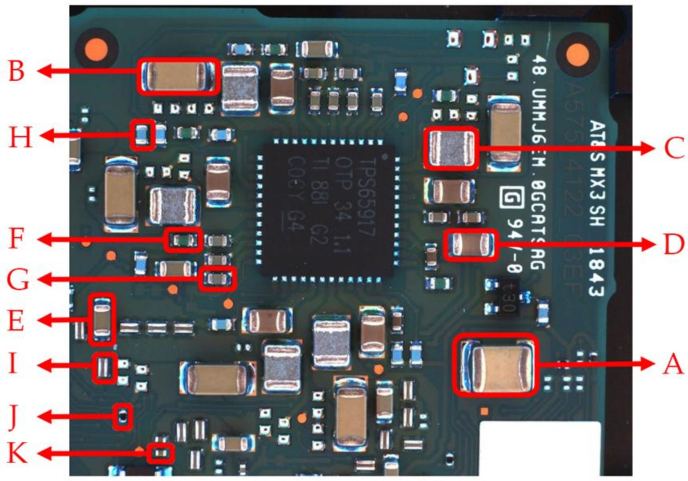
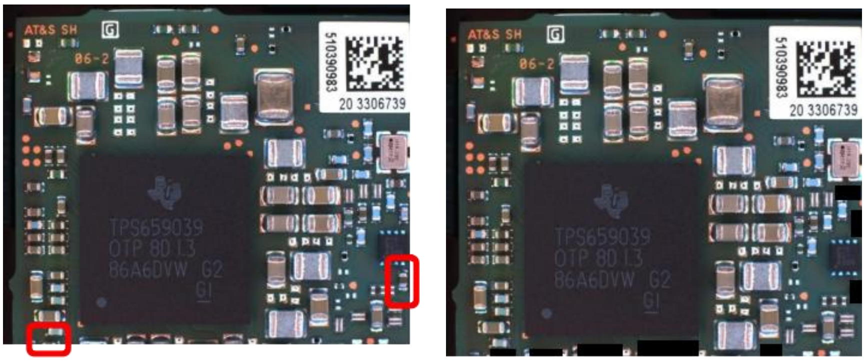



**Fig. 4** Classification diagram of component categories

The second stage is to divide the components into several methods and models. The experiment has 180 image samples. Since each image needs to be manually marked with software before training, it is not easy to obtain training samples. There are as many as five components to be marked on each image. There are more than a dozen pieces, 15 pieces of training data and 160 pieces of verification data are taken out randomly. The number of components in these 15 images. YOLO is the object that has been marked for training, and each component can be regarded as a training session. The experiment is divided into Table 2, according to the appearance and size of the components. There are 3 ways, and the group in each way is a detection model.

PCB image pre-processing there are two reasons why the image needs pre-processing. One is that some components of the image may be cut, and the other is that the components are too close to the edge of the image. It may happen that some images have components and some are absent, as shown in Fig. 5(a). The image is pre-processed to mask the cut components and the components adjacent to the edge, as shown in Fig. 5(b).

Post-processing of data includes calibration and positioning, drawing component outlines, and calculating the number of components. After picking out the component by YOLO, the category information and coordinate position of the component are obtained. Since the captured images will have some errors, each image needs to be corrected, and each PCB has its positioning point, which can be used for correction, but because the PCB has been divided into 9 images, it is no longer available. The method currently used is the end point and start point of the circuit on the PCB, and a two-point vector is used for correction. The corrected image can obtain the coordinate position of the component with low error, and then calculate whether the number of components is correct and mark its outline. If all the components are correct, it is regarded as a good product. If there are missing parts, the image will be picked out and saved for subsequent re-inspection.




(a) Close to the edge and cut element	(b) Masked image

**Fig. 5.** Image pre-processing

## 4. Experimental Results and Discussion

The experiment is trained by the classification method of model training. It is divided into two stages. The first stage is to test its recognition rate, and the second stage is to test its compatibility. The following will display the experimental results and analyze.

### 4.1. Parameters Setting and Testing Experiment

YOLO sample and parameter setting, the experiment has 180 image samples, which are divided into 15 as training data and 160 as verification data. The number of training components is 650, the number of anchors is 9, the batch size is 3, and the learning rate is iterative. If the number of times is large, the initial learning rate is 0.001. The number of iterations stops after 100 iterations after Loss is no longer reduced, and the model weight is stored when loss is lower. YOLO model training results and recognition rate, according to the 165 verification images, if the image contains the specified component of the model, and the component is all detected, there is no missed inspection or multiple inspections, and the number is correct, the identification is deemed correct. Otherwise, the identification is incorrect. The training results and recognition rate of the model are displayed below, and the confidence score of each model is set to 0.5. Table 1 uses one model identification for all components, and there are verification images of missing components among the 160 verification images up to 148 images, as shown in Fig. 6 (a), the correct identification images are all images with fewer components, as shown in Fig. 6 (b), and from the training error of model in Fig.7, it can be seen The loss has decreased, but the convergence is not good, and the recognition rate of this model is low.

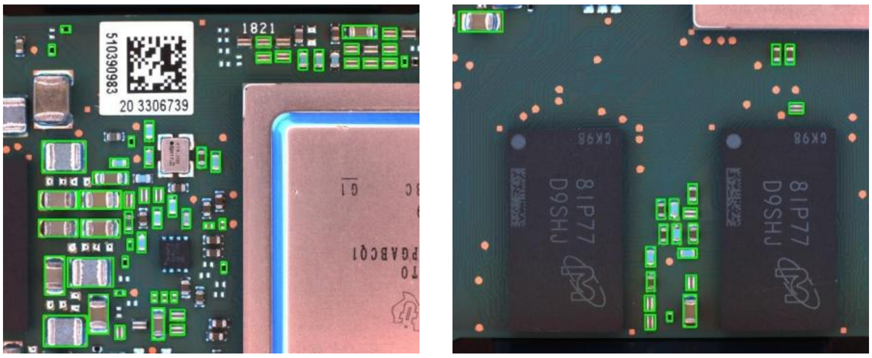
PCB Defect Detection recognition rate experiment: To judge the quality of a PCB detection model is not only to judge the detection effect of a single type of target. Using the original Yolo network respectively, due to the particularity of the defect detection recognition rate is added to the experiment. The evaluation standard is characterized by mean of recognition rate (RR) or identification rate. The higher the value of RR, the better the detection effect and the stronger the comprehensive performance of the PCB for the detection of different types of targets. The RR calculation formula is shown in formula 1.

$$mRR = \frac{1}{N}\sum_{i \in N} RR(i) \qquad (1)$$

In the formula, RR represents the average recognition rate, N represents the number of detected target types, and RR is the mean value of different types of RRs. The test results are shown in table 1. The network improved in this paper has better performance in the data level.

**Table 1.** Model training results of method A1

| Model | Identification component | Loss | Identification rate (%) |
|---|---|---|---|
| A1 | A,B,C,D,E,F,G,H,I,J,K | 46.7917 | 0.103 |



(a) Component missed image (b) Unmissed image

**Fig. 6.** Image recognition result of model No. A1

Table 2 shows the training results of two models with large and small components. The recognition rate of the model number A2-1 has reached 0.909, as shown in Fig. 8(a), 15 images were missed out of the 160 verification images, but the model number A2-2 was identified the rate is only 0.460, and there are many missed detections. As shown in Fig. 8(b), the model A2-1 converges well. It can be seen that the loss decreases more steadily. Higher and unstable decline, this model has a low recognition rate.

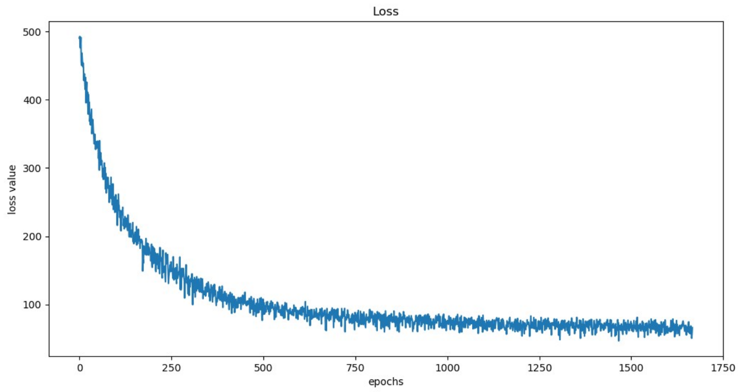
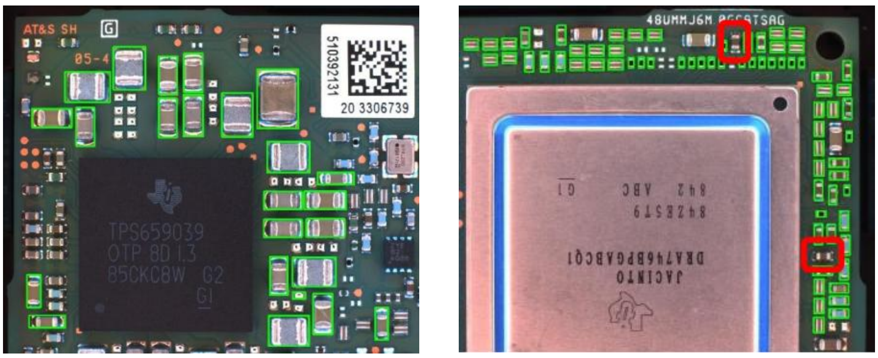



**Fig. 7.** The training error diagram of the model number A1

**Table 2.** Model training results of Method A2

| Model | Identification component | Loss | Identification rate (%) |
|---|---|---|---|
| A2-1 | A,B,C,D,E | 13.387 | 0.909 |
| A2-2 | F,G,H,I,J,K | 53.5868 | 0.460 |




(a) Identification result of model A2-1 (b) Missed image of model A2-2

**Fig. 8.** Image recognition results of A2-1 model and A2-2 model

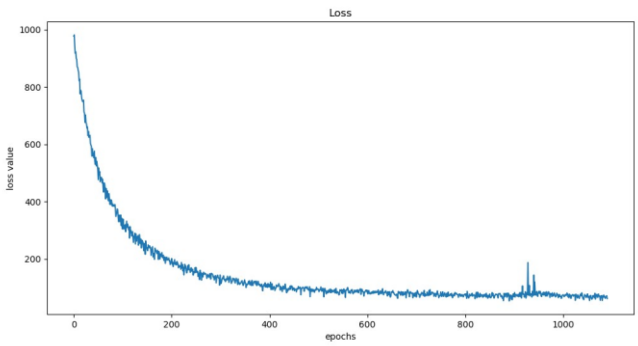
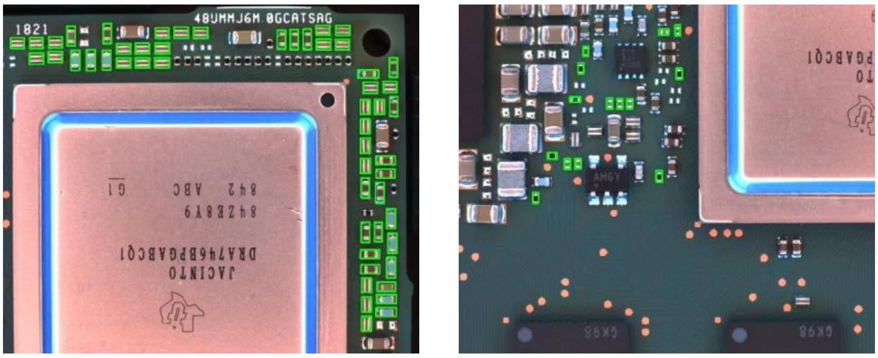



**Fig. 9.** The training error diagram of the model number A2-2

Table 3 shows the training results of the components divided into three models: large, medium and small, the model number A3-1 is the same as the model number A2-1. The model has a high recognition rate. Compared with the model A2-2 as Fig. 9, the model A3-2 and the A3-3 model have a higher recognition rate. The recognition rate, the model converges well. Fig. 10 shows the identification results of the two models. From the training error graphs in Fig. 11, the loss convergence is relatively stable and low.

**Table 3.** Model training results of Method A3

| Model | Identification component | Loss | Identification rate (%) |
|---|---|---|---|
| A3-1 | A,B,C,D,E | 13.387 | 0.92 |
| A3-2 | F,G,H,I, | 23.9571 | 0.89 |
| A3-3 | J,K | 12.3623 | 0.88 |



(a) Identification result of model A3-2 (b) Identification result of model A3-3

**Fig. 10.** The image recognition result of model A3-2 and model A3-3

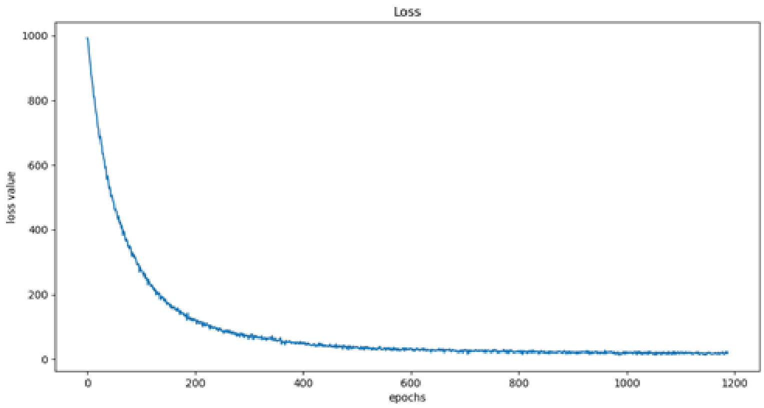



**Fig. 11.** Training error graph of model A3-3

The three methods proposed for component detection are the method in which all components are identified as one model. A1 component division the method of identifying two models of large and small components. A2 the method of identifying components into three models of large, medium and small. Table 4 shows the detection time and overall identification rate of the three methods. The overall identification rate is to use the full model of this method to identify all components. , If there is no missed inspection or multiple inspections in the verification image, and the number is correct, the identification is considered correct. Otherwise, it is an identification error. In two or three models, there will be a problem of missing verification images. The recognition rate is lower than that of the single-number model, but the recognition rate of method A3 is still higher. Among 160 verification images, 121 images were successfully recognized.

**Table 4.** Recognition time and recognition rate of each method

| Method | Number of models | Recognition time/second (median) | Overall recognition rate (%) |
|---|---|---|---|
| A1 | 1 | 0.07 | 0.20 |
| A2 | 2 | 0.14 | 0.64 |
| A3 | 3 | 0.21 | 0.83 |

## 4.2. Discussion

Improve PCB recognition rate: From the experimental process, it can be seen that the three model identification effects of method A3 are better. This method is used to adjust the model parameters to improve its identification rate. For the other two methods, the identification rate is low, and more subjective reasons are proposed. In methods A1 and A2, one model or two models are used for identification. When one model is used for training, it is found that the loss convergence is not good. The possible reason is that the amount of data is not enough, or the similarity between components is too high Caused.

The effect of changing it to two models is improved, and then it is changed to three model detection. The factor that does not continue to use more model identification is that the identification time of each image is not expected to be too long, which affects the detection cycle of the entire detection system ( Cycle time).

The parameters are adjusted based on the three models in Mode 3, and the algorithm is not adjusted. Adjust the content as 1. Find more suitable Anchors. 2. Find a more appropriate confidence score. 3. Enlarge the input image to improve the recognition rate. The first model with acceptable convergence (identification A, B, C, D, E) still has its confidence score, and the poorer convergence model (identification F, G, H, I) reduces its confidence score to Improve the detection rate, and the third model (identification J, K) has the problem of component multi-judgment. The confidence score of component multi-judgment is between 0.5 and 0.6. Therefore, the confidence score is increased to avoid component multi-judgment.

Situation to increase the detection rate. Table 5 shows the detection components, confidence scores and detection rates corresponding to the three models.

**Table 5.** Identification results of each model after fine-tuning the confidence score

| Method | Number of models | Confidence score | Recognition rate |
|---|---|---|---|
| A1 | A,B,C,D,E | 0.5 | 0.93 |
| A2 | F,G,H,I | 0.2 | 0.94 |
| A3 | J,K | 0.6 | 0.89 |
| Overall recognition rate | | 0.92 | |

In the case of a fixed confidence score, if the input image is enlarged, the final output tensor will also be increased to improve the recognition rate, mainly for the two smaller components numbered J and K, and the verification image will be increased to 450. Fig. 12 shows the changes in the detection time and overall recognition rate after taking measures to increase the image input size.

After the model is adjusted, the input image size is 1024x1216x3, 9 anchors, the recognition time is 0.208 seconds, and the recognition rate has been increased from 0.732 to 0.922. The total number of components is 10500, and the number of missing components is only 30. The total components are recognized, the rate is 0.997. According to the current recognition status, the K component has the lowest recognition rate. For the missing image of the K component, the improvement method is to increase the number of samples to improve its convergence effect, or increase the image input size to increase the output image. However, it still depends on the performance of the computer.

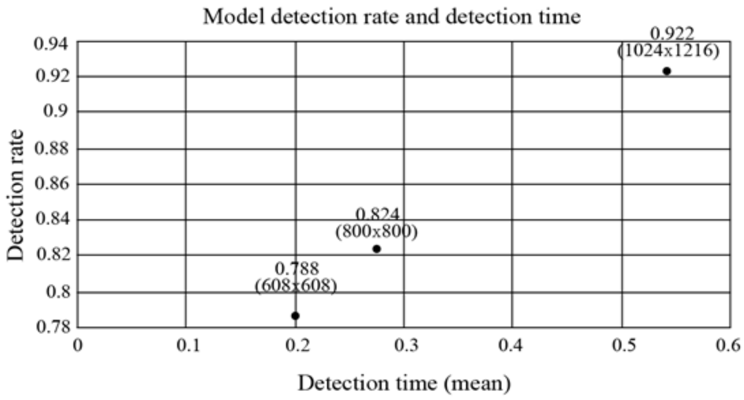



**Fig. 12.** The change of the recognition rate after fine-tuning the image size

### 4.3. PCB Testing Inheritance

According to the training results of the model, this study will test whether the model can be effectively used on PCBs with different light, different backplane colors, or other material numbers. The experimental samples have 8 kinds of images with different background, light or material numbers, each of which has 9 images, for a total of 72 images. The recognition rate is 0.903. We use a small number of samples for training, and uses a large number of verification samples to test its recognition rate and detection compatibility. The recognition rate is 0.922 and the compatibility recognition rate is 0.903. If a larger number of training samples are used, and the input image size can be increased, each type can be effectively improved. The confidence score of the component and the overall recognition rate, according to this research, can show that the use of YOLO is an effective compatible model, which can be used on PCB with different light rays, backplanes, and part numbers.

### 4.4. Comparison of Different Detection Methods

Because the defect of the PCB is the identification target of this paper, the Recognition Rate (RR) of the model is the most important for the identification task of PCB in this paper. The recognition rate can be characterized by RR. The same data set is used in this paper, and R-CNN, SSD, and Yolo are used for PCB detection. The results are shown in Table 6.

The Mean Average Precision (mAP) is our indicator for evaluating model performance our main indicator for evaluate model performance. It is the average of the Average Precision (AP) values of C different defects, and it reflects the accuracy of defect detection as formula 2.

$$mAP = \frac{\sum_{i=1}^{C} AP_i}{C} \qquad (2)$$

**Table 6.** Defect detection results of different method

| Different detection methods | Recognition Rate (RR)% | Mean Average Precision (mAP) |
|---|---|---|
| Proposed method | 92.2 | 90.1 |
| SSD | 86.9 | 86.1 |
| R-CNN | 91.2 | 86.2 |
| RetinaNet | 88.5 | 91.1 |

As can be seen from Table 6, the RR score of Yolo in proposed paper is the highest, reaching 92.2%, followed by R-CNN, reaching 91.2%, indicating that this paper has better detection performance, is faster than other networks. From the perspective of RR, the improved performance is more balanced, it can accelerates the inspection speed and better serve the inspection task of PCB defects, while ensuring the accuracy.

## 5. Conclusions

Due to the price of ICT machines is too expensive and each inspection line needs to purchase a piece of equipment, and AOI encounters different products and requires different inspection algorithms. PCB surface components are large amounts more complex, and the algorithm is difficult to compile. The research findings deep learning which has achieved considerably in image recognition, has helped a major breakthrough in visual inspection. The contribution of this paper and the results can reduce the fatigue of manual visual inspection and labor costs. Improve detection efficiency and the consistency of testing. Effectively compatible with other PCBs with different lights, backplanes, and material numbers. This detection method can effectively divide components to replace manual visual inspection, and the cost is reduced. It solves the expensive condition of the original ICT machine and is effectively compatible with other PCBs to replace the problem of reprogramming algorithms on AOI. Future work: The current FOV is too small to cover the whole PCB, so it is recommended to increase the camera pixels and improve the computer equipment specifications to facilitate model training. On the PCB, there are not only defects on the components, but still has many surface defects such as open circuits, short circuits, tin tips, scratches, cracks, and foot deformations. It is recommended that the future research direction can use deep learning to detect more surface flaws, such as scratches, foot deformations, and short circuits, and test its recognition rate and compatibility. The limitation is due to the high price of commercially available printed circuit board inspection machines, the use of Automated Optical Inspection (AOI) can reduce the additional purchase cost of the inspection machine, but it still is due to the different products of the PCB, and the algorithms behind it will also be followed. Change the detection compatibility is low, and often cannot be used on the next product.

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