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Detection and Classification of Printed Circuit Board Assembly Defects Based on Deep Learning

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Keywords: printed circuit board assembly, defect detection, defect classification, deep learning.

ABSTRACT

In recent years, the booming artificial intelligence technology has been gradually introduced into the defect inspection system with optical images in various industrial production lines, which has improved the precision and yield of products. However, for test images with multiple defects, the fault detection rate is still very high. In addition, the need to identify the processing lack through defect classification is also increasing. In order to enhance the accuracy and intelligence of using optical images to detect and classify the compound defects on printed circuit board assembly (PCBA), this study compared the performance of several deep learning models in dealing with multi-defect images. Through the comparison of test performance, it is suggested to use YOLOv3 model to overcome the challenges of diversity and complexity of PCBA components. Based on YOLOv3, 800 images randomly containing 10 kinds of PCBA defects were trained. Each sample contains an unequal number of defects. The training results show that the mean average precision (mAP) in defect classification is as high as 97.47%. In the test experiment, 60 sample images were inspected and compared with the results of manual inspection. Experimental results show that the error rates of PCBA defect detection and classification are as low as 0% and 2.42% respectively, which indicates that the optimized YOLOv3 model can be applied to industrial production lines to achieve the goal of high-precision detection and classification of composite defects.

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INTRODUCTION

Automatic equipment integrating machine vision and motion control has been widely used in the production process for real-time inspection and quality control (Celaschi et al., 2019; Hung et al., 2018; Liao et al., 2018). Neural networks have also been introduced into automation systems, which has promoted the development of industry to a high-speed, efficient and high-quality production mode (Chang et al., 2008; Lim et al., 2019; Liu et al., 2019; Sun et al., 2019). Although the introduction of artificial intelligence has improved the speed and accuracy of product defect detection, high misjudgment rate is still a major problem in many complex manufacturing processes.

Recently, deep learning technology has been gradually introduced into various industrial applications, with excellent performance in image, audio and text information (Chen et al., 2019; der Mauer and Behrens, 2019; Zhong et al., 2019). By learning from a large amount of existing data and constantly updating the data and revising the prediction results through the backpropagation algorithm, the goal of various defect characteristics can be accurately quantified through the continuous learning process. However, when there are several different types of defects in an inspection image, reducing erroneous judgment of defects is still a big challenge. The most typical case is the defect detection of PCBA on the production line.

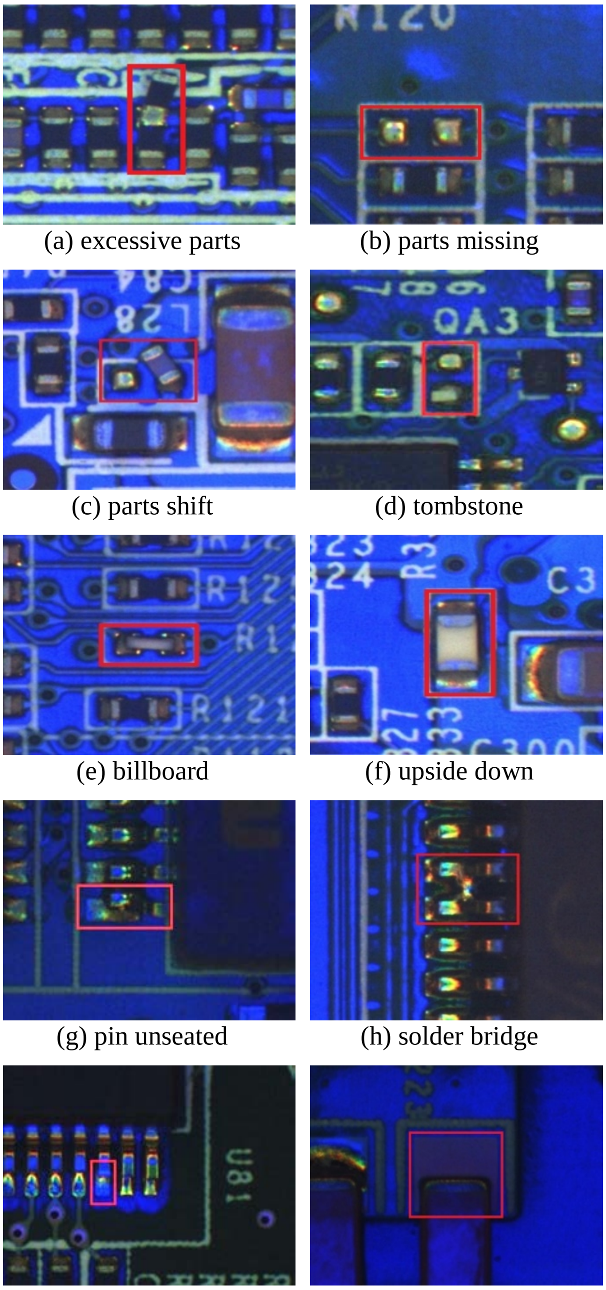
A PCBA is a circuit board in which all components and parts, including resistors, capacitors, inductors, IC, etc., are soldered and mounted on a printed circuit board. In order to reduce the cost and achieve the goal of high efficiency and high quality production, automated optical inspection (AOI) technology has been widely used in PCBA production line. However, due to the diversity and complexity of components on PCBA, there are still not a few non-defective boards that are judged by AOI as defective products, and vice versa. Therefore, it is necessary to improve the intelligence of AOI instrument applied to PCBA defect inspection.

In this study, deep learning technology is applied to PCBA defect detection to overcome the diversity and complexity of composite defects. Here, four kinds of currently recognized most powerful deep learning models with object detection characteristics are selected to compare the performance of these four frameworks in detecting PCBA composite defects. 800 images randomly containing 10 kinds of PCBA defects collected by a commercial AOI system for training. Then, another 50 defect images containing 124 defects collected by the AOI instrument were used for a preliminary test experiment. All images were checked with manual inspection and the experimental results show that YOLOv3 has the best effect in PCBA defect classification. Therefore, further discussions were carried out to improve the performance of YOLOv3 in detecting and classifying PCBA defects. The final training results for defect classification of the 10 types of defect show that the mAP (Oksuz et al., 2018) at the Intersection over Union (IoU) (Kosub, 2019) of 0.5 is improved to 97.47%, showing its ability to accurately detect and classify complex and compound defects on PCBA. Finally, a test was carried out on the 50 defective images and another 10 defect-free images. Experimental results show that all 124 defects were detected, of which only 3 were incorrectly classified and no defect-free image was misjudged as defective. This indicates that the adoption of deep learning technology can greatly improve the yield of defect detection and reduce the manufacturing cost.

It is worth mentioning that one of the major challenges in this work is the means to process large amounts of data, so it is more practical to use parallel computing architecture and graphics processing unit (GPU) for fast data calculation (Ye et al., 2018). In this study, a dual GTX1080 GPU card was applied. Experimental results showed that it took only 14 ms on average to recognize each image. This shows that although deep learning technology needs a long time to train, the actual inspection speed on product line is acceptable.

DEFECT TYPE AND DEFINITION

The sample images with PCBA defects were captured by a commercial AOI instrument (TR7500 SII, Test Research Inc., Taipei, Taiwan). In this study, ten kinds of defects were selected for inspection, as shown in Figure 1. Among them, “excessive parts” means there are redundant parts or foreign bodies on the board, “parts missing” refers to parts that should be installed on the board but are missing, “parts shift” means that the part deviates from the expected orientation or position, “tombstone” is a defect caused in the welding process in which one end of an element is welded to a solder joint while the other end is erected up like a tombstone due to uneven stress on both ends, “billboard” means that the part is rotated 90 degrees so that it is welded to the pad laterally, “upside down” means that the front and back of the element is reversely welded on the pad, “pin unseated” means that the foots of the part is bent or not flat on the tin plate, “solder bridge” refers to the short circuit caused by the connection of two independent solder joints due to soldering, “solder insufficient” means insufficient amount of tin thereon and may affect the welding strength, “missing solder” refers to that tin does not stick to the preset position on the pad.



(a) excessive parts (b) parts missing
(c) parts shift (d) tombstone
(e) billboard (f) upside down
(g) pin unseated (h) solder bridge
(i) solder insufficient (j) missing solder

Figure 1. Images of 10 kinds of PCBA defects.

PEFFORMANCE COMPARISON OF DEEP LEARNING MODELS

Defect Detection Using Image Classification Models

Based on the images obtained from AOI, the performance of defect detection using four image classification learning models, including Inception-Resnet-V2 (Szegedy et al., 2017), Resnet_50 (He et al., 2016), Inception V3 (Szegedy et al., 2016), and VGG19 (Simonyan and Zisserman, 2015), is first studied. The size of each 2D PCBA image extracted by the commercial AOI system is 640*480 pixels. In these models, each sample can only contain one type of defect, so each type of defect must be trained and tested individually. Five kinds of defect images including parts missing, shifting, upside down, billboard and tombstone were adopted for testing, to compare the defect detection accuracy of the four models. The training sample consists of 5000 defective images and 5000 flawless images, which are obtained by expanding 30 pixels around the tested assembly and then adjusting the size of each image to 200*200 pixels. The epoch and learning rate are 30 and 0.0001 in training, respectively. After training, 1507 flawed images and 249 flawless images were randomly selected from AOI pictures for testing. The test results are shown in Table 1. Where, "TP" means that the flawless image is judged to be flawless, "TN" means that the defective image is judged to be defective, "FN" means that the flawless image is judged to be defective and there will be trouble in lowering the yield rate, and "FP" means that the defective image is judged to be flawless and is directly related to the reduction in product quality. The test accuracy is obtained by dividing the number of correctly judged samples with total samples, which is about 80%. The false rate is determined by FP/(TN+FP), which represents the probability of the defective board passing through. Since defect detection is performed on images with 640*480 pixels obtained from the commercial AOI system, one image may contain a plurality of defects. Therefore, the four deep learning models that can only deal with single defect detection are not competent, resulting in a high false rate. It is necessary to look for other models with higher performance.

Table 1. Comparison of defect detection performance of four image classification models.

Deep Learning Model	Inception-Resnet-V2	Resnet_50	Inception V3	VGG19
Epoch	30	30	30	30
Learning Rate	0.0001	0.0001	0.0001	0.0001
AUC	0.857	0.840	0.864	0.797
True Positive (TP)	1,177	1,214	1,238	1,249
False Negative (FN)	330	293	269	258
False Positive (FP)	46	68	60	98
True Negative (TN)	203	181	189	151
Test accuracy	78.6 %	79.4 %	81.3 %	79.7 %
False Rate (Defect)	18.5 %	27.3 %	24.1 %	39.4 %

Defect Classification Using Object Detection Models

In order to meet the needs of detecting and classifying composite defects in images, deep learning models with object detection features are then considered. At present, deep learning models based on object detection are mainly divided into two categories. In the first, a series of candidate boxes are generated, and then the samples are classified into appropriate boxes using convolutional neural networks. The other one does not generate candidate boxes, but directly converts the object positioning into a regression process. The former excels in detecting and positioning accuracy, while the latter is good at calculating speed. In this paper, four models are adopted and compared, among which Faster R-CNN (Ren et al., 2015) and R-FCN (Dai et al., 2016) belong to the former, SSD (Liu et al., 2016) and YOLOv3 (Redmon and Farhadi, 2018) belong to the latter. 800 images with 1354 defects were selected from AOI for training. Each image randomly contains 1 to 5 different defect, including 10 defect categories shown in Figure 1. The quantity of various defect features in the training samples is shown in Table 2.

Table 2. Quantity of PCBA defects used for training.

Defect Type	Quantity
excessive parts	70
parts missing	327
parts shift	114
tombstone	54
billboard	84
upside down	98
pin unseated	109
solder bridge	102
solder insufficient	243
missing solder	153
Total	**1354**

The training parameters and obtained classification precision in the training process are shown in Table 3. For the frameworks of Faster R-CNN and R-FCN, the short side of the input image should be greater than 600 pixels for feature extraction. Therefore, the input images are first enlarged from the original size of 640 × 480 pixels to 800 × 600 pixels. Due to the characteristics of the network structure, the training batch can only be 1. When the learning rate is 0.0001 and the Intersection over Union (IoU) threshold is 0.5, the obtained optimal mAP for defect classification by using Faster R-CNN is 53.71% after 160,000 iterations, and the optimal mAP of R-FCN is 60.43% after 120,000 iterations. For the learning models of SSD and YOLOv3, the images are scaled to 300 × 300 pixels and 416 × 416 pixels respectively before being input into the neural network. Their batch is set at 8. Under the same learning rate and IoU threshold, after 300 epochs of training, the optimal mAP for defect classification using SSD is 57.96%, while that of YOLOv3 is 71.09% after 200 training epochs.

Table 3. Comparison of training parameters and accuracy of four object detection models.

Deep Learning Model	Faster R-CNN	R-FCN	SSD	YOLOv3
Input Image Size	800 × 600	800 × 600	300 × 300	416 × 416
Training Batch	1	1	8	8
Learning Rate	0.0001	0.0001	0.0001	0.0001
Intersection over Union	0.5	0.5	0.5	0.5
Iteration Number	160,000 cycles	120,000 cycles	300 epochs	200 epochs
mAP	53.71%	60.43%	57.96%	71.09%

After the training, another 50 PCBA images with 124 defects were taken as test samples, and the amounts of various defects in images are shown in Table 4. The test results show that the number of defects correctly classified by Faster R-CNN, R-FCN, SSD and YOLOv3 is 65, 73, 67 and 85 respectively. As shown, YOLOv3 learning model has achieved the highest accuracy both in training and testing, indicating that it can be used as a priority object detection framework for PCBA defect diagnosis. In addition, the average processing time of each image in the four models is 85 ms, 43 ms, 12 ms and 14 ms respectively. This show that YOLOv3 is also very effective in image inspection speed.

Table 4. Quantities of PCBA defects used for testing.

Defect Type	Quantity
excessive parts	5
parts missing	33
parts shift	18
tombstone	6
billboard	10
upside down	14
pin unseated	11
solder bridge	7
solder insufficient	13
missing solder	7
Total	**124**

DETECTION AND CLASSIFICATION OF PCBA DEFECTS UTILIZING YOLOv3

The above results show that YOLOv3 model can achieve fast and high-precision inspection results for the detection and classification of complex defects such as PCBA. Therefore, this study will further optimize the training parameters of YOLOv3 framework to improve the detection accuracy. In order to improve the accuracy of detection and classification, we must first increase the number of training samples. The original 800 defect images were rotated four times continuously at 90 degrees and combined with their mirror images to obtain a total of 6,400 training samples and 10832 defects. At a fixed learning rate of 0.0001, it took about 83 hours for 125 epochs to complete the deep learning training via the accelerating operation of two GTX1080 GPU cards. The training result is shown in Figure 2, where the accuracy $mAP_{0.5}$ at IoU of 0.5 is significantly improved from 71.09% to 91.25%, showing that more data can undoubtedly bring better and more accurate training performance.

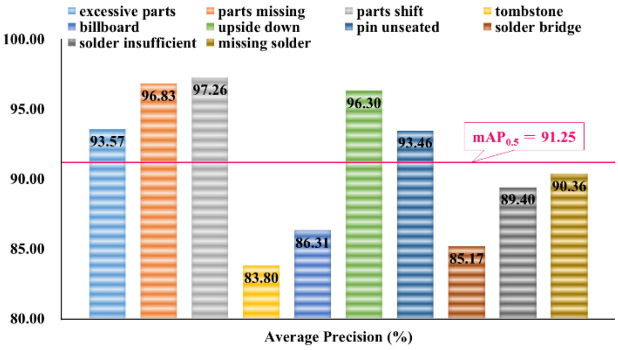


Figure 2. Preliminary training precision of PCBA defect classification using YOLOv3.

YOLOv3 model can also use multi-scale training process to detect targets of different sizes. With the change of the quantity, scale and data set of detected feature images, the size of anchor box needs to be adjusted accordingly. In this study, 9 prior anchor boxes with sizes of (17×18), (28×24), (36×34), (42×44), (56×51), (72×66), (90×95), (92×154) and (139×281) were obtained based on K-means cluster (Oksuz et al., 2018). Then the multi-scale training was conducted under the randomly scaled input images of 288~448 (multiples of 32) pixels. After 116 hours of 105 epochs training, the optimal training performance of $mAP_{0.5}$ reaches 95.50%, as shown in Figure 3.

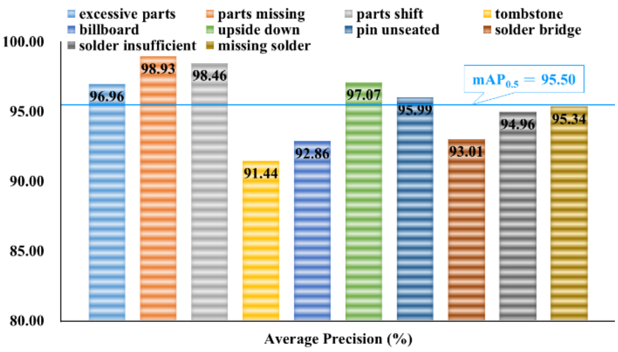


Figure 3. Average precision of PCBA defect classification using multi-scale method.

Another important parameter that can improve the accuracy of deep learning is the learning rate, which will greatly affect the weight of the network through adjusting the loss gradient (Bottou, 2012). Generally speaking, the smaller the learning rate, the higher the accuracy, which ensure that the local minimum value will not be missed. However, this also means that it will take longer for the network to converge. In this study, a training process with dynamic learning rate scheme instead of the previous fixed rate was suggested. At the beginning of the training, a large learning rate of 0.001 was set to converge rapidly. As the training process progressed, once the total loss value did not decrease for 5 consecutive epochs, the rate was multiplied by the decay argument of 0.1. Therefore, the learning rate was gradually reduced until the value dropped to 0.000001 and there was no more improvement for the loss, then the training was completed. Figure 4 shows the change between loss and training epoch under the learning rate decay scheme. The whole training process is completed after 70 epochs take about 78 hours, showing that the dynamic learning rate scheme shortened the training time. In addition, the average classification accuracy $mAP_{0.5}$ of the training model is also increased to 97.47%, as shown in Figure 5.

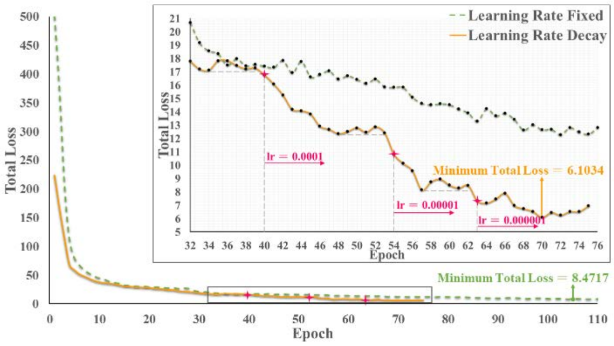


Figure 4. Changes of loss with training epoch under learning rate decay scheme.

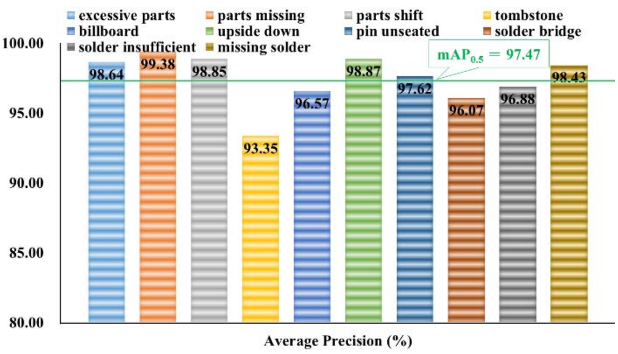


Figure 5. Average precision of PCBA defect classification based on multi-scale training and learning rate decay scheme.

In addition to the original 50 images containing defects, another 10 images without defects were also added to the following test experiment. Table 5 is a confusion matrix of test results of the 60 images based on the above training results. The matrix shows that no defect-free image was misjudged as defective, and only 3 of 124 defects were incorrectly classified. This means that the accuracy of defect detection is as high as 100%, and the accuracy of defect classification is 97.58%. The average processing time of each image is the same as the previous 14 ms. Figures 6 are illusions of some test images. Figure 6(a) shows no defect category is marked in the defect-free image, indicating that the model classifier is not over-detected. Figures 6(b) and 6(c) show that whether there is only one defect or a plurality of defects in an image, it can be correctly detected by the model classifier, which not only defines the position of each defect, but also indicates the probability of each defect category. Figure 6(d) shows that even multiple defects are located at the same position, the model can also correctly frame the location and mark multiple tag categories. Figures 6(e) and 6(f) are 2 misclassified images. Figure 6(e) shows that there is a “pin unseated” defect in the image, but the model identified it as a “solder bridge” with a probability of 77.62%. The main reason is that the two defects have similar characteristics, which leads to misjudgment. Figure 6(f) shows that three defects were detected in the image, and the positions of these defects were accurately framed. However, one of them was identified as “upside down” with a probability of 76.25%, which should be a misjudgment of the defect “billboard”. It can be seen from these examples that misclassification may occur when the recognition probability is lower than 80%.

Table 5. Confusion matrix of PCBA defect classification results.

		Defect Category										
		excessive parts	parts missing	parts shift	tombstone	billboard	upside down	pin unseated	solder bridge	solder insufficient	missing solder	pass image
Classification Result	excessive parts	5	0	0	0	0	0	0	0	0	0	0
	parts missing	0	33	0	1	0	0	0	0	0	0	0
	parts shift	0	0	18	0	0	0	0	0	0	0	0
	tombstone	0	0	0	5	0	0	0	0	0	0	0
	billboard	0	0	0	0	9	0	0	0	0	0	0
	upside down	0	0	0	0	1	14	0	0	0	0	0
	pin unseated	0	0	0	0	0	0	10	0	0	0	0
	solder bridge	0	0	0	0	0	0	1	7	0	0	0
	solder insufficient	0	0	0	0	0	0	0	0	13	0	0
	missing solder	0	0	0	0	0	0	0	0	0	7	0
	pass image	0	0	0	0	0	0	0	0	0	0	10

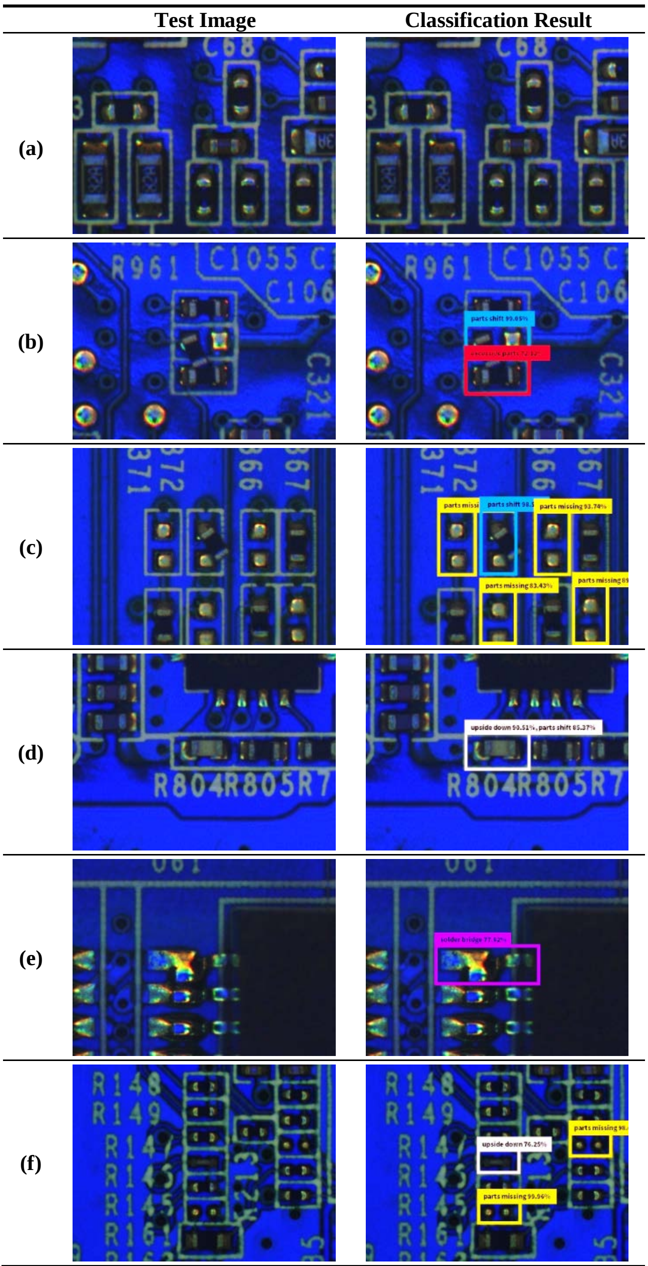


Figure 6. Illustration of some test images: (a) An image without defects; (b) An image has two defects; (c) An image has several defects; (d) An image has two defects at the same position; (e) Defect "pin unseated" is misjudged as "solder bridge"; (f) An image has three defects, one of which is that the "billboard" is misjudged as "upside down".

CONCLUSIONS

This study developed a compound defect detection and classification system based on YOLOv3 deep learning model. Based on K-means clustering, multi-scale training is carried out to realize the initialization of 9 anchor boxes, and operation is carried out under random scaling input images of 288~448 pixels to match the detection of defects of different sizes. Learning rate decay strategy is adopted to reduce the training time and increase training precision. Experimental results show that the accuracy of PCBA multi-defect detection and classification is as high as 100% and 97.58% respectively. Through the parallel computing of a dual GPU card, the detection time of each image is 14 ms, which indicates that the developed system can achieve intelligent and fast inspection in the subject of composite defect detection. In the future, the defect classification catalogue may be integrated with the optical inspection results to propose the influencing factors in the manufacturing process.

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基於深度學習的印刷電路板元件組裝瑕疵檢測與分類

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摘 要

近年來，蓬勃發展的人工智慧技術逐漸被引入到各種工業生產線的光學影像瑕疵檢測系統中，提高了產品的精度和良率，但對於同時含多種瑕疵的測試影像而言，其檢測錯誤率仍然很高；此外，通過瑕疵分類來了解與處理加工缺失的需求也在增加。為了提高以光學影像執行印刷電路板元件組裝複合瑕疵檢測和分類的準確性和智慧性，本研究比較了多種深度學習模型處理複合瑕疵圖像的性能，透過對各種模型檢測效能的測試比對，建議使用 YOLOv3 模型來克服 PCBA 元件的多樣性和複雜性的挑戰。本研究採用了包含 10 類 PCBA 瑕疵的 800 幅影像進行訓練，其合計有 1354 個瑕疵，在 YOLOv3 的基礎上，基於 K-means 聚類方法進行多尺度訓練，並以 288~448 像素隨機縮放輸入影像之尺寸，以匹配不同尺度之瑕疵的檢測；並採用學習率衰減策略，可同時縮短訓練時間與提高訓練精度，最終訓練結果顯示此 10 類瑕疵分類的平均精度均值高達 97.47%。實際測試時係以另外 10 幅無瑕疵影像與 50 幅含 124 個瑕疵的影像執行瑕疵的檢測與分類，並與人工檢測結果進行了對比，顯示 PCBA 複合瑕疵檢測和分類的錯誤率分別為 0%和 2.42%，驗證了參數優化後的 YOLOv3 模型確實可以應用於業界產線上，達到複合瑕疵高精度檢測和分類目標。